Essays in Corporate Finance

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A dissertation presented

by

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to

The Department of Economics

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

in the subject of

Economics

Harvard University

Cambridge, Massachusetts

May 2016

Dissertation Advisor: Author:
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Abstract

This dissertation contains three chapters. In the first chapter, which is joint work with Paul Gompers and Steven Kaplan, we survey 79 private equity (PE) investors with combined assets under management of more than $750 billion about their practices in firm valuation, capital structure, governance, and value creation. Investors rely primarily on internal rates of return and multiples to evaluate investments. Their limited partners focus more on absolute performance as opposed to risk-adjusted returns. Capital structure choice is based equally on optimal trade-off and market timing considerations. PE investors anticipate adding value to portfolio companies, with a greater focus on increasing growth than on reducing costs. We also explore how the actions that PE managers say they take group into specific firm strategies and how those strategies are related to firm founder characteristics.

The second chapter, co-authored with Efraim Benmelech, Nittai Bergman, and Anna Milanez, identifies a new channel through which bankrupt firms impose negative externalities on non-bankrupt peers. The bankruptcy and liquidation of a retail chain weakens the economies of agglomeration in any given local area, reducing the attractiveness of retail centers for remaining stores leading to contagion of financial

distress. We find that companies with greater geographic exposure to bankrupt retailers are more likely to close stores in affected areas. We further show that the effect of these externalities on non-bankrupt peers is higher when the affected stores are smaller and are operated by firms with poor financial health.

In the third chapter, using a novel dataset that allows me to capture the education and career trajectories of over 250,000 employees of 224 bank holding companies, I find that banks with shorter employee tenures and higher fractions of MBAs, top school graduates, and job jumpers performed more poorly during the Great Recession. This relationship is driven by the predisposition of these banks to take on greater risk. These same workforce measures also explain banks' performance in the 1998 crisis. Taken together, my results suggest that investigating workforce measures could be a step towards quantifying components of risk culture or strategy that contribute to financial institutions' vulnerability to crisis.

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Acknowledgments

I would like to thank Effi Benmelech, Paul Gompers, and Andrei Shleifer for their extensive guidance and support. I cannot imagine having gone through this process without them, and have learned so much from their mentorship and co-authorship. Their encouragement of me, especially during the job market, meant more than I will ever be able to express, and I am eternally grateful to them.

I also thank Nittai Bergman, John Campbell, George Chacko, Lauren Cohen, Shawn Cole, Sanjiv Das, Robin Greenwood, Sam Hanson, Steve Kaplan, Reinout Koopmans, Josh Lerner, Alonso Perez-Kakabadse, David Scharfstein, Arthur Segel, Hersh Shefrin, Jeremy Stein, Lawrence Summers, David Webb, Glen Weyl, Yuhai Xuan, Akram Yosri, and Jean-Pierre Zigrand for their advice and support throughout my graduate school career. Additionally, I am grateful to seminar participants here at Harvard for their thoughtful comments on all stages of this work.

I am also deeply appreciative to the faculty of my undergraduate school—the International College of Economics and Finance, Higher School of Economics—especially Alexis Belianin, Jeffrey Lockshin, Krister Sairsingh, and Sergei Yakovlev.

Personally, I am grateful to the Sarin family, especially Bufar, without whom I am confident this dissertation would not have come to fruition. I also thank my peers and colleagues in the Harvard Economics Department, who have made the past several years here in Cambridge the highlight of my educational career. Finally, I am grateful to my parents who are my first—and foremost—champions.

To my brother

Chapter 1

What Do Private Equity Firms Say They Do?[1]

1.1 Introduction

The private equity (PE, buyout) industry has grown markedly since the mid-1990s, and academic research has increasingly focused on the effects of private equity.[2] What have been less explored are the specific analyses and actions taken by PE fund managers. This paper seeks to fill that gap. In a survey of 79 private equity firms managing more than $750 billion in capital, we provide granular information on PE managers' practices in determining capital structure, valuing transactions, sourcing deals, governance, and operational engineering. We also explore how the actions that private equity managers say they take group into specific firm strategies and how those strategies are related to firm founder characteristics.

Recent academic research has provided accumulating evidence that private equity investors have performed well relative to reasonable benchmarks. At the private equity

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[1] Co-authored with Paul Gompers and Steven Kaplan.

[2] We classify private equity as buyout or growth equity investments in mature companies. Private equity as we define it in this paper is distinct from and does not include venture capital (VC) investments. Many papers in the literature study both venture capital and buyout investments, particularly those related to performance for limited partners. We decided to pursue PE firms instead of VC firms for several reasons. First, PE firms take different actions and invest in different companies than VC firms. Studying the asset classes together would have made the paper even longer and more unwieldy. In contrast, performance can be compared across asset classes, making it sensible to study VC and PE together. Second, PE firms are arguably subject to more controversy about what they do and whether they create value. And, finally, PE is a much larger asset class.

fund level, Harris, Jenkinson and Kaplan (2014), Higson and Stucke (2012), Robinson and Sensoy (2013), and Ang, Chen, Goetzmann, and Phalippou (2013) all find that private equity funds have outperformed public equity markets net of fees since the mid-1980s. The outperformance versus the Standard & Poor's (S&P) 500 in Harris, Jenkinson, and Kaplan is on the order of 20% over the life of a fund and roughly 4% per year. Consistent with that net of fee performance, Axelson, Sorensen, and Strömberg (2013) find outperformance of over 8% per year gross of fees.

At the private equity portfolio company level, Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda (2014) find significant increases in productivity in a large sample of US buyouts from the 1980s to early 2000s. Cohn and Towery (2013) find significant increases in operating performance in a large sample of US buyouts of private firms. Kaplan (1989) finds significant increases in public to private deals in the 1980s. Cohn, Mills, and Towery (2014) and Guo, Hotchkiss, and Song (2011) find modest increases in operating performance for public to private buyouts in the 1990s and early 2000s, although Guo, Hotchkiss, and Song find large increases in company values.

From Gompers and Lerner (1999), Metrick and Yasuda (2010), and Chung, Sensoy, Stern, and Weisbach (2012), we also know that the compensation of the partners at the private equity funds creates strong incentives to generate high returns, both directly and through the ability to raise subsequent funds. Strong performance for some funds has led to very high compensation for those investors.

The high-powered incentives combined with the largely positive empirical results are consistent with PE investors taking actions that are value increasing or maximizing. Kaplan and Strömberg (2009) classify three types of value-increasing actions: financial engineering, governance engineering, and operational engineering. These value-increasing actions are not necessarily mutually exclusive, but certain firms likely emphasize some of them more than others.

In financial engineering, PE investors provide strong equity incentives to the management teams of their portfolio companies. At the same time, leverage puts pressure on managers not to waste money. In governance engineering, PE investors control the boards of their portfolio companies and are more actively involved in governance than public company directors and public shareholders. In operational engineering, PE firms develop industry and operating expertise that they bring to bear to add value to their portfolio companies.

Despite the growth in private equity, only a few papers have studied the actions that private equity investors take. Early papers by Baker and Wruck (1989) and Baker (1992) explored value creation in individual cases. More recently, Acharya, Gottschalg, Hahn, and Kehoe (2013) study portfolio company performance and relate that performance to PE firm and partner characteristics. Much still remains unknown. No paper examines detailed levers of value creation across financial, governance, and operational engineering.

In this paper, we further explore what PE investors do by reporting the results of a survey of private equity investing practices. First, we identify and tabulate the key decisions that private equity investors make. The range of decisions is significantly more detailed than has been examined in the prior literature. Our survey is structured around examining decisions that support financial, governance, or operational engineering. Second, we attempt to categorize distinct strategies that private equity firms employ.

We survey 79 PE investors (with a total of more than $750 billion of private equity assets under management (AUM) as of the end of 2012). We obtain complete answers from 64 of these firms (representing more than $600 billion of private equity AUM). The sample represents private equity firms across a spectrum of investment strategies, size, industry specialization, and geographic focus. We ask the PE investors questions about financial engineering—how they value companies and how they think about portfolio company capital structures and management incentives; governance engineering—how they think about governance and monitoring; and operational engineering—how they think about value creation, both before and after closing the transaction. We also ask questions about the organization of the private equity firms themselves.

Despite the prominent role that discounted cash flow valuation methods play in academic finance courses, few PE investors use discounted cash flow or net present value techniques to evaluate investments. Instead, they rely on internal rates of return (IRRs) and multiples of invested capital (MOICs). This contrasts with the results in Graham and Harvey (2001), that chief financial officers (CFOs) use net present values as often as internal rates of return. Furthermore, few PE investors explicitly use the capital asset price model (CAPM) to determine a cost of capital. Instead, PE investors target a 22% internal rate of return on their investments on average (with the vast majority of target rates of return between 20% and 25%), a return that appears to be above a CAPM-based rate. We offer several potential explanations for this seemingly ad hoc approach to investment analysis.

We also asked the PE investors how their limited partners (LPs) evaluate the performance of the private equity investors. Surprisingly, the PE investors believe that their LPs are most focused on absolute performance than on relative performance or alphas. This is also puzzling given that private equity investments are equity investments, some of which had been publicly traded prior to a leveraged buyout. Such investments carry significant equity risk, suggesting that equity-based benchmarks such as public market equivalents (PMEs) are appropriate.

Our results on capital structure are more consistent with academic theory and teaching. In choosing the capital structures for their portfolio companies, PE investors appear to rely equally on factors that are consistent with capital structure trade-off theories and those that are consistent with market timing. The market timing result is consistent with the results in Axelson, Jenkinson, Strömberg, and Weisbach (2013; henceforth AJSW (2013)), although the capital structure trade-off theory result is not. These results are, however, somewhat different from those in Graham and Harvey (2001), who find that CFOs focus on financial flexibility.

Financial and governance engineering also appear to be important. In terms of portfolio company management, PE investors expect to provide strong equity incentives to their management teams and believe those incentives are very important. They regularly replace top management, both before and after they invest. And they structure smaller boards of directors with a mix of insiders, PE investors, and outsiders. These results are consistent with research on value-enhancing governance structures that have been identified in other settings.

Finally, PE investors say they place a heavy emphasis on adding value to their portfolio companies, both before and after they invest. The sources of that added value, in order of importance, are increasing revenue, improving incentives and governance, facilitating a high-value exit or sale, making additional acquisitions, replacing management, and reducing costs. On average, they commit meaningful resources to add value, although a great deal of variation exists in how they do so.

We take the responses to the various questions about individual decisions and analyze how various decisions are related to each other by employing cluster analysis and factor analysis. Essentially, we use cluster analysis to explore whether private equity firms follow particular strategies. We find that the answers to our survey cluster into categories that are related to financial engineering, governance engineering, and operational engineering, that is, the levers of value creation highlighted in Kaplan and Strömberg (2009).

We then consider how those strategies are related to firm founder characteristics. Firms with founders who have a financial background tend to focus more on financial engineering, while those who have a previous background in private equity and, to a lesser extent, operations tend to focus more on operational engineering.

In what follows, we assume the PE investor responses are accurate and interpret the survey accordingly. The PE investors filled out the survey with the assurance that they would not be identified and that their responses would be aggregated so they could not be identified. No individual firm thus has any incentive to report overly positive or otherwise inaccurate responses. Doing so will not benefit any one individual firm directly. We recognize, however, that some PE investors could report overly positively on some questions in the hope that the PE industry will be cast in a better light. We discuss how such behavior could affect our results.

The paper proceeds as follows. Section 1.2 relates the paper to the existing literature. Section 1.3 discusses the research design and the sample. Sections 1.4–1.6 examine PE firms' financial, governance, and operational engineering practices. Section 1.7 explores the organizational structure of firms. Section 1.8 discusses potential concerns stemming from the survey research design. Section 1.9 explores how the actions that PE managers say they take are reflected into specific firm strategies. Section 1.10 relates those strategies to firm founder characteristics. Section 1.11 concludes.

1.2 Related literature

This paper is related to several strands in the literature. Our survey allows us to evaluate whether and how different corporate finance theories are applied in practice by investors with extremely high incentives to perform and who also have the highest level of education from top business schools. Large academic literatures study firm valuation, capital structure, and governance. Do what private equity investors say they do conform to what researchers think should be done? Our paper explores how these financial decisions are related to firm characteristics.

Research on capital structure has spawned large numbers of papers that seek to explain how firms set their debt and equity structures. Three primary theories receive prominence in the literature. First, the trade-off theory of Myers (1977) predicts that the amount of debt that a firm raises is a balance between the value creation of interest tax shields and the expected cost of financial distress. It is optimal for firms to raise additional debt until the marginal tax shield benefit of the additional dollar of debt equals the marginal increase in expected cost of financial distress. The trade-off theory corresponds to what most introductory finance courses teach about debt policy. Second, the pecking order theory (Myers, 1984) predicts that firms prefer to raise as much safe debt as possible. Once safe debt is exhausted, firms raise risky debt then equity to fund projects. Third, Baker and Wurgler (2002) propose a theory of capital structure that depends on firm managers timing markets based upon the mispricing of debt or equity. When interest rates are perceived to be particularly low relative to fundamentals, firms increase borrowing, and when equity markets are overvalued, firms would tend to raise more equity. We seek to assess how much of private equity firm managers' leverage decisions are governed by each of these theories.

Governance engineering has been another major area of research in corporate finance. Jensen and Meckling (1976) were among the first scholars to note that agency conflicts exist between managers (who typically own small fractions of equity in the firms that they manage) and outside shareholders. Governance engineering involves creating a better alignment of incentives between managers and shareholders or providing better oversight that can limit empire building and opportunistic behavior. Gompers, Ishii, and Metrick (2003) demonstrate that broad measures of corporate governance are related to public company performance and valuation. Jensen and Murphy (1990) create a framework to measure the incentive effects of equity ownership for firm managers. Kaplan (1989) examines management ownership changes in a sample of leveraged buyouts from the 1980s and finds that ownership substantially increases on average.

Incentive compensation has been a particularly important area of governance research. Jensen (1986) argues that managers of publicly traded firms typically own too little equity to make them sensitive to maximizing shareholder value. Private equity managers who are aware of these issues seek to align incentives through increases in managerial equity ownership.

Boards of directors are often viewed as an important governance tool to monitor managers on behalf of shareholders. Fama and Jensen (1983) discuss the role of boards and how boards should function. Hermalin and Weisbach (1998) examine the determinants of board structure and argue that board structure tends to be endogenously determined to minimize conflicts with shareholders. Coles, Daniels, and Naveen (2008) examine how board size is related to both firm characteristics and firm performance. In general, the literature argues that small boards dominated by outsiders perform better. We examine board strategy issues for private equity investors.

We also examine specific strategies around improvement in operating performance. Many private equity firms market to their investors and potential portfolio companies their ability to increase value by improving operating performance. Kaplan (1989) was the first to find improved operating performance after firms undergo a leveraged buyout. Kaplan and Strömberg (2009) summarize subsequent research largely confirming that private equity investments are associated with improvements in operating performance or productivity. While little research has identified the key operating levers that private equity managers pull to improve performance, several papers have examined the effects of private equity on the operational performance of the companies they own. More recently, Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda (2014) use US Census data to study a large sample of US buyouts and find that they are associated with increased productivity. Cohn and Towery (2013) use income tax data to study a large sample of US buyouts and find improvements in operating margins. The exceptions to these positive results are public to private transactions. Cohn, Mills, and Towery (2014) and Guo, Hotchkiss, and Song (2011) find modest, but insignificant, increases in operating margins in US public to private transactions.

In doing these analyses, we view this paper as a complement to the survey papers of Graham and Harvey, beginning with Graham and Harvey (2001).[3] Graham and Harvey survey chief financial officers to understand how they make capital budgeting, capital structure, and other decisions. They compare their survey findings of practice with the recommendations or insights from different academic theories. In this paper, we do the same. We view this survey as particularly interesting because private equity investors have been so successful (both in terms of generating attractive returns for investors and compensation for their managers), have strong incentives to maximize shareholder value, and, because of those incentives and compensation, very likely attract talented individuals. Furthermore, a large percentage of private equity investors have been trained at prominent business schools. In recent years, positions in private equity firms have been among the most coveted for graduating master of business administration (MBA) students. A PitchBook 2013 survey showed that a small number of elite business schools accounted for the majority of new hires in private equity. As such, we might expect that private equity investors' practices would approximate what financial economists believe is theoretically (and empirically) value maximizing.

Finally, our paper is complementary to Da Rin and Phalippou (2014), who survey a large sample of PE limited partners. Their survey includes questions on the criteria PE limited partners use in choosing PE investments. Da Rin and Phalippou, however, have relatively little to say about the internal decision-making and strategies of the general partner.

[3] See also Brav, Graham, Harvey, and Michaely (2005) and Graham, Harvey, and Rajgopal (2005).

1.3 Sample and design

In this section, we discuss the implementation of the survey and the sample of firms used in the study.

1.3.1 Design

We created the survey to determine what PE investors say that they do. We also attempted to design the survey to compare what those investors do relative to what is taught at business schools. We initially tested the survey on three PE investors in the summer of 2011. We revised the survey to reflect some ambiguities in our questions and to add some questions. The final survey contains 92 questions and is available on Paul Gompers's website.[4]

1.3.2 Delivery and response

We began to distribute the survey to PE investors in the fall of 2011. We distributed it to firms in which one of us knew or was introduced to a senior investment professional. We continued to identify potential PE investors in 2012. We received our last survey response in the winter of 2013. The vast majority of survey responses, therefore, were received in 2012.

We contacted a total of 136 PE firms. We sent survey links to 106 investors at these firms who expressed an interest in the survey. Of these, 79 filled out some part of the survey and 64 completely filled out the survey. The response rate of roughly 50% is much higher than the response rate for other surveys. Graham and Harvey (2001) obtain a response rate of 8.9% for CFOs, and Da Rin and Phalippou (2014) obtain a response rate of 13.8% for PE limited partners.

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[4] See http://people.hbs.edu/pgompers/GKM_PE_survey.pdf

1.3.3 Private equity firm characteristics

Table 1.1 provides some summary statistics for the firms of the PE investors who responded to the survey. We obtained cumulative assets under management in private equity, performance of the most recent primary fund (if available), and age of each private equity firm in the sample as of December 2012 from Preqin. [5] Information on firms not covered by Preqin is taken from firm websites and media articles.

Table 1.1: Private equity firm respondents

	N	Mean	25th percentile	Median	75th percentile	Standard deviation
AUM (millions of dollars)	79	9,548.6	750.0	3,400.0	11,000.0	15,021.1
IRR over benchmark (percent)	58	2.7	−3.9	0.9	6.9	11.8
Multiple of invested capital	58	1.3	1.2	1.3	1.5	0.3
Age (years)	79	19.5	12.0	19.0	26.0	10.5
Firms with						
- office(s) only in the US	44					
- office(s) outside the US	35					

Notes: This table describes the sample PE investor respondents. Reported are assets under management (AUM), performance of most recent fund (if available), and age of each private equity firm in the sample as of December 2012 from Preqin. Information on firms not covered by Preqin is taken from firm websites and the media. We also use the results of the current survey to determine office locations of firms in the sample. IRR = internal rate of return.

The table shows a large variation in the size of the firms as measured by assets under management. The mean AUM is just under $10 billion. A quarter of the firms have AUM under $750 million and a quarter have AUM above $11 billion.

Our overall sample of 79 firms represents firms with a total of more than $750 billion in AUM. Our sample of 64 firms that completed the entire survey represents a total of more than $600 billion in AUM. We have solid coverage of the largest PE firms.

[5] This measures cumulative AUM for the PE firm, not the size of the most recent fund.

Each year, *Private Equity International* (PEI) ranks the top PE firms globally by AUM. Our (fully completed) sample has 11 of the top 25 in PEI's 2012 list. Given this, our results are reflective of a meaningful fraction of the PE industry.

The table also indicates that Preqin has performance data for the most recent fund for 58 of the sample PE firms. The average fund in the sample has an IRR that is 2.7% above Preqin's benchmark IRR for the same vintage year. The median fund is 0.9% above. This suggests that our sample is largely representative of the PE fund universe, at least in terms of performance. If anything, we could have a small bias towards better performers. We do not believe such a bias would influence our results in a meaningful way. If anything, our sample of firms would be expected to employ better practices than other PE firms and as such their actions should conform more closely to what finance research and courses prescribe.

Despite the apparent representativeness of the sample and the relatively high response rate, we recognize that the sample is potentially selected. This is unavoidable given our requirement that we have an introduction to a senior person and given that PE firms have limited disclosure requirements. Given the large total AUM our sample PE firms control, the survey represents a meaningful fraction of the PE industry.

Table 1.2 presents the distribution of enterprise values of the portfolio companies in which the PE firms invest. The sample has good representation of many different PE firm enterprise values and covers the broad spectrum of PE investing. The table suggests that almost one-sixth of portfolio company investments by the sample PE firms have enterprise values exceeding $1 billion and almost 12% have enterprise values below $25 million.

Table 1.2: Enterprise value

			AUM		IRR		Age		Offices	
Enterprise value	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
< $25 million	11.8	0.0	19.0	5.5***	4.4	9.4	6.2	16.1**	16.2	6.3**
$25 million – $100 million	26.3	10.0	44.4	10.4***	16.8	23.5	20.1	31.0	33.4	17.5**
$100 million – $500 million	28.7	22.0	28.6	28.8	29.3	31.9	31.4	26.6	27.6	30.1
$500 million – $1 billion	16.8	10.0	5.2	27.0***	22.0	19.8	19.4	14.9	12.7	21.9**
> $1 billion	16.4	0.0	2.8	28.3***	27.4	15.3	22.9	11.4**	10.2	24.1**
Number of responses	79	79	37	42	29	29	34	45	44	35

Notes: This table describes the enterprise value of portfolio companies of the sample private equity (PE) investors. Question is: "What fraction of the companies you invest in have the total enterprise value within the following ranges?" The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table 1.3 confirms that the private equity investors in our sample are primarily buyout and growth equity investors, not venture capital investors. Over 90% of the PE investors invest in buyouts and almost 75% invest in growth equity. These add up to more than one because many PE investors invest in both buyouts and growth equity. A minority of the sample firms, particularly the older and larger ones, also invests in distressed investments and PIPEs (private investments in public equities).

Table 1.3: Type of investments

		AUM		IRR		Age		Offices	
Type of investment	Mean	Low	High	Low	High	Old	Young	Local	Global
LBOs	90.1	82.9	97.2**	92.3	96.2	93.9	86.8	92.7	86.7
Growth equity	73.2	74.3	72.2	65.4	73.1	69.7	76.3	73.2	73.3
Distress	29.6	17.1	41.7**	26.9	34.6	30.3	28.9	19.5	43.3**
PIPEs	32.4	20.0	44.4**	38.5	38.5	45.5	21.1**	31.7	33.3
Other	8.5	8.6	8.3	3.8	7.7	9.1	7.9	7.3	10.0
Number of responses	71	35	36	26	26	33	38	41	30

Notes: This table describes the types of investments considered by the sample private equity (PE) investors. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. LBOs = leveraged buyouts; PIPEs = private investments in public equity.

Finally, consistent with our survey delivery method, Table 1.4 indicates that over three-quarters of the surveys were completed by a senior PE executive; one with the title general partner, managing partner, or managing director. As such, we feel that the responses are very likely indicative of firm practices employed within the PE organizations broadly.

Table 1.4: Private equity individual respondents

		AUM		IRR		Age		Offices	
Title	Mean	Low	High	Low	High	Old	Young	Local	Global
General partner or director	25.3	21.6	28.6	31.0	31.0	32.4	20.0	25.0	25.7
Managing partner	22.8	35.1	11.9**	13.8	20.7	20.6	24.4	29.5	14.3
Managing director	29.1	18.9	38.1	37.9	20.7	26.5	31.1	22.7	37.1
Chief financial officer	3.8	5.4	2.4	3.4	6.9	2.9	4.4	6.8	0.0
Other	19.0	18.9	19.0	13.8	20.7	17.6	20.0	15.9	22.9
Number of responses	79	37	42	29	29	34	45	44	35

Notes: This table describes the title of the individual filling out the survey at the sample PE investor firms. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

We also used the PE firm websites to collect the names and educations of all of the partner-level executives at our sample PE firms. We used the titles partner, managing partner, managing director, senior managing director, founder, chief executive officer (CEO), chairman, head, and principal. We identified 767 such individuals. Of these, almost two-thirds have either an MBA or a doctor of law degree (juris doctor or JD)—435 or 57% have an MBA and 54 or 7% have a law degree. Of those with an MBA, 167 (38%) are from Harvard Business School, 52 (12%) are from University of Chicago Booth School of Business, 39 (9%) are from Stanford Graduate School of Business, 32 (7%) are from the Wharton School of the University of Pennsylvania, and 23 (5%) are from Columbia Business School. These figures indicate that the top executives at these firms are highly educated and a very large fraction of them have degrees from what would be considered the top graduate schools. Once again, we believe that, given the educational background of the sample, our PE firms would likely employ industry best practices in their investment process. At the same time, we could have oversampled Harvard and Chicago alums while undersampling Wharton alums.[6]

1.4 Financial engineering

This section explores how PE firms state that they employ different components of financial engineering.

1.4.1 Valuation: capital budgeting

In this subsection, we consider how PE investors value the companies in which they invest or, equivalently, evaluate the attractiveness of those investments. A substantial corporate finance literature has developed around capital budgeting. Firms decide which projects to undertake based upon a variety of investment rules. Much of the early finance research established that optimal decision making for firms should be based on net present value analyses.[7] Finance theory is clear that estimating expected future cash flows from an investment, then using a discount rate that is derived from an explicit asset pricing model (e.g., CAPM or Fama and French three-factor model) should lead to better investment decisions when compared with alternatives such as internal rate of return or payback analysis (e.g., multiple on invested capital). The theory, therefore, predicts or suggests that private equity investors should be more likely

[6] The PitchBook database finds that Harvard Business School alums make up 26%; Wharton alums, 11%; and Chicago alums, 7% of all PE firm professionals. See "Harvard, 4 Other Schools, Make Up Most MBAs at PE & VC Firms," http://blog.pitchbook.com/harvard-4-other-schools-make-up-most-mbas-at-pe-vc-firms/

[7] For example, see Brealey, Myers, and Allen (2013).

to use discounted cash flow methods. Our results allow us to explore how investment decision-making criteria at PE firms compares with the framework implied by finance theory.

1.4.1.1 Valuation: evaluation methods

The survey asks the PE investors to identify different methods they use to evaluate the overall attractiveness of a deal. First, we asked which metrics they use, giving them the choice of gross internal rate of return, multiple of invested capital, adjusted present value (APV) discounted cash flow (DCF), weighted average costs of capital (WACC) DCF, comparable company EBITDA (earnings before interest, taxes, depreciation, and amortization) multiples, and free cash flow return to equity. Panel A of Table 1.5 reports the results. The vast majority of the PE investors rely on gross IRR and MOIC. Over 70% also incorporate comparable company multiples. In contrast, relatively few PE investors use DCF methods. In sum, less than 20% use APV or WACC-based DCF methods to evaluate investments. Second, we asked the PE investors to rank their reliance on the different methods. Again, as Panel B of Table 1.5 indicates, IRR (in particular) and multiple approaches are the overwhelming favorites while net and adjusted present value approaches lag far behind.

We also directly asked private equity managers how they calculate their WACC. Only 18 (or 27%) of the PE investors describe performing a calculation that can be generously considered to approximate a traditional, CAPM-based approach. At the same time, 27 said they did not use WACC and another 10 said "not applicable," indicating, that they, too, do not use WACC. Overall, then, at least 55% of the PE investors appear not to use WACC at all.

Table 1.5: Deal evaluation metrics and methods

			AUM		IRR		Age		Offices	
Metric/method	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel A: Deal evaluation metrics										
Gross IRR	92.7	100.0	88.5	97.0	99.9	96.9	100.0	86.4**	94.2	90.5
Multiple of invested capital	94.8	100.0	92.1	97.7	99.1	93.3	96.1	93.7	95.5	93.8
Adjusted present value (APV) DCF	9.3	0.0	7.1	11.5	9.3	7.3	3.9	13.9	10.5	7.6
WACC-based DCF	10.9	0.0	9.3	12.5	5.5	15.2	8.9	12.5	9.4	12.9
Comparable company EBITDA multiples	71.7	100.0	71.4	72.1	63.0	90.7**	75.9	68.1	76.7	64.8
Free cash flow return to equity	43.8	33.0	29.7	58.3***	45.2	43.7	44.4	43.2	40.7	48.1
Other	13.8	0.0	10.3	17.4	7.0	21.7	12.1	15.3	8.3	21.4
Number of responses	67	67	34	33	25	23	31	36	39	28
Panel B: Deal evaluation methods										
Accounting rate of return	0.6	0.0	0.9	0.2	0.7	0.7	0.5	0.7	0.6	0.5
Adjusted present value	0.9	0.0	0.6	1.2	0.6	0.8	0.5	1.3	0.8	1.0
Discounted payback period	1.7	0.0	1.7	1.6	1.3	1.3	1.3	1.9	1.9	1.3
Earnings multiple approach	6.1	8.0	6.0	6.1	5.5	6.2	5.4	6.7	6.1	6.1
Hurdle rate	3.6	0.0	3.7	3.5	4.4	2.0**	3.4	3.8	3.7	3.5
Internal rate of return	9.2	10.0	9.0	9.4	9.8	9.1	9.5	9.0	8.9	9.6
Net present value	2.8	0.0	2.1	3.4	3.7	2.0	2.5	3.0	2.4	3.3
Payback period	2.4	0.0	2.4	2.4	2.1	2.1	2.5	2.3	2.8	1.7
Profitability index	0.9	0.0	1.0	0.8	0.8	0.3	0.3	1.5**	0.5	1.4
Other	2.1	0.0	2.5	1.6	2.2	2.8	2.3	1.9	1.9	2.3
Number of responses	67	67	34	33	25	23	31	36	39	28

Notes: Panel A presents the percentage of deals for which the sample private equity (PE) investors use different methods to evaluate an investment. Panel B provides the average ranking of different methods that the sample PE investors use to evaluate an investment, where 10 is the highest and 1 is the lowest. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. DCF = discounted cash flow; WACC = weighted average cost of capital; EBITDA = earnings before interest, taxes, depreciation, and amortization.

These results indicate that PE investors do not frequently use net present value or DCF techniques. This contrasts markedly with the results in Graham and Harvey (2001) for CFOs. They find that CFOs rely on net present value techniques roughly as frequently as IRR and that large company CFOs rely heavily on the CAPM to determine their cost of capital.

Our results for PE investors also contrast with the methods taught in MBA finance courses at all top business schools as well as typical valuation analyses seen in investment banker fairness opinions for mergers and acquisitions. CAPM-based discounted cash flow analyses are the primary method taught and used in those settings.

Finally, in their IRR calculation, the PE investors clearly evaluate cash flows to leveraged equity. Arguably, this, too, contrasts with the usual academic advice in MBA finance courses to evaluate and discount cash flows to an all-equity firm. This also raises questions as to whether limited partners understand the returns are leveraged.

1.4.1.2 Years of forecasts

In evaluating any investment, investors typically forecast the cash flows of that investment over some period of time. We asked the PE investors to tell us the time horizon of the investment cash flows they evaluate. Figure 1.1 indicates that the great majority of PE investors, almost 96% of our sample, use a five-year forecast horizon. At the end of the five years, they typically calculate a terminal or exit value. This indicates that PE investors do not find it productive or valuable to forecast cash flows for more than five years.

Graham and Harvey (2001) do not appear to have asked this question so we cannot compare our results with theirs. While we did not explicitly ask why PE firms use five years as the predominant forecasting horizon, most PE firms expect to hold their investments for approximately five years. As such, forecasting cash flows over five years approximates the PE firm's time horizon. Several investors have told us that using a standard time period, such as five years, allows the PE firms to compare different investments on an equal footing. That explains why each firm would use a standard horizon, but not why almost all firms would use the same five-year horizon.

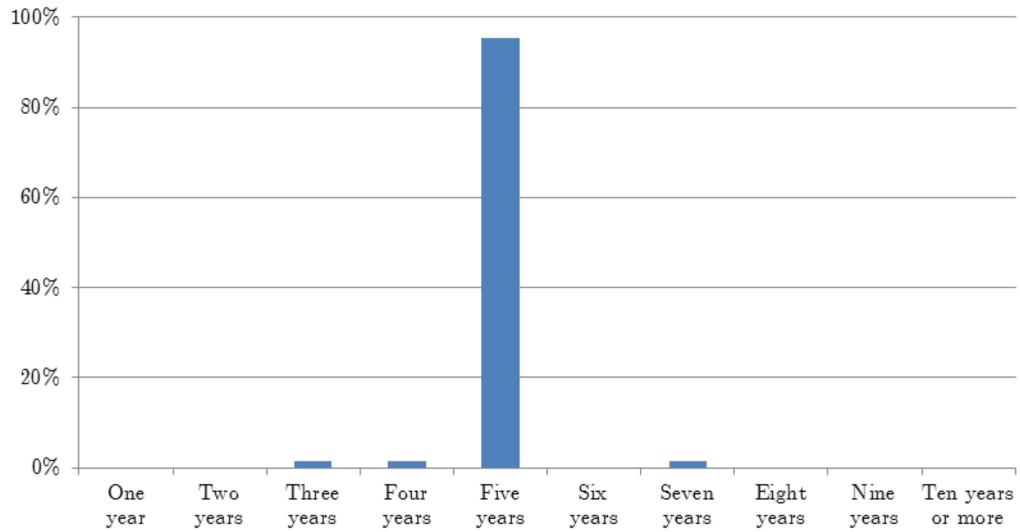

Figure 1.1: Years of forecasts used by the sample private equity investors.

1.4.1.3 Discount of management forecasts

When PE investors evaluate an investment, they usually begin with a set of management forecasts. It seems natural to assume that the PE investors would view those forecasts as optimistic. Accordingly, we asked the PE investors whether they typically adjusted management's forecasts. We asked them to measure this as a fraction of EBITDA, a measure of pre-tax cash flow.

Table 1.6 shows that PE investors typically discount management forecasts. For the 44 PE investors who answered this question explicitly, the average and median discounts are 25% and 20%, respectively. Another 11 of the PE investors who did not provide a number indicated that the discount varied with the circumstances of individual deals.

Table 1.6: Discount to management's EBITDA forecasts

	Mean	Median	AUM Low	AUM High	IRR Low	IRR High	Age Old	Age Young	Offices Local	Offices Global
Discount to management's EBITDA	0.25	0.20	0.27	0.21	0.26	0.25	0.21	0.28	0.25	0.25
Number of responses	44	44	27	17	15	14	20	24	29	15

Notes: This table reports the discount that the sample private equity (PE) investors normally take to management's EBITDA (earnings before interest, taxes, depreciation, and amortization) in their pro forma models. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence.

1.4.1.4 Exit value or terminal value

To evaluate the economics of an investment, the PE investors need to estimate a value for their investment (or, equivalently the portfolio company) at the expected time of exit, which is almost always five years into the investment. This valuation can be done in (at least) three ways: (1) using the (discounted) value of a growing perpetuity of the final year cash flow in a CAPM framework, (2) using the value of comparable or similar public companies, and (3) using the value of acquisitions or transactions involving comparable or similar companies.

Panel A of Table 1.7 indicates that PE investors are much more likely to use comparable methods—both publicly traded companies and transactions—than discounted cash flow methods. Fewer than 30% of the PE investors use a growing perpetuity methodology. The percentage increases for larger PE firms but remains below 35%. The other category is dominated by 11 firms (or 16%) indicating that they use the entry multiple (the EBITDA multiple the PE investor paid for the company) to calculate the exit multiple.

Table 1.7: Terminal value calculation and comparable company selection

			AUM		IRR		Age		Offices	
	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel A: Terminal value calculation										
Comparable companies	81.4	100.0	75.3	87.7	81.3	88.6	87.3	76.3	78.2	85.8
Comparable transactions	71.4	99.0	67.8	75.0	73.2	80.3	79.5	64.4	76.1	64.8
DCF-based growing perpetuity	27.3	10.0	20.5	34.3	28.1	16.4	26.6	27.9	21.0	36.0
Other	25.6	0.0	33.5	17.4	20.7	31.1	22.8	27.9	28.7	21.3
Number of responses	67	67	34	33	25	23	31	36	39	28
Panel B: Comparable company selection										
Industry	96.9		96.9	97.0	95.8	100.0	100.0	94.1	94.6	100.0
Riskiness	49.2		34.4	63.6**	54.2	56.5	45.2	52.9	48.6	50.0
Size	84.6		87.5	81.8	87.5	87.0	90.3	79.4	86.5	82.1
Growth	73.8		75.0	72.7	79.2	69.6	77.4	70.6	75.7	71.4
Margins	66.2		59.4	72.7	83.3	65.2	67.7	64.7	62.2	71.4
Capital intensity	52.3		31.3	72.7***	62.5	52.2	51.6	52.9	51.4	53.6
Geography	56.9		43.8	69.7**	58.3	69.6	67.7	47.1	48.6	67.9
Other	4.6		6.3	3.0	4.2	8.7	3.2	5.9	8.1	0.0
Do not use comparables	3.1		3.1	3.0	4.2	0.0	0.0	5.9	5.4	0.0
Number of responses	65		32	33	24	23	31	34	37	28

Notes: Panel A reports the fraction of deals for which the sample private equity (PE) investors use different methods to calculate the exit value or terminal value of the model. Panel B shows the determinants of the selection that the sample PE investors use for comparable companies for multiples valuation or exit value. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. DCF = discounted cash flow.

Panel B explores how the PE investors choose the comparable companies they use. Industry and firm size are the most important criteria they match on, with growth, margins, and geography next in importance. Setting the exit multiple equal to the entry multiple is also consistent with matching on firm industry and size. Firm riskiness ranks seventh among the different criteria. Again, PE investors appear to be skeptical of using measures of risk that have strong foundations in academic finance.

1.4.1.5 IRR and MOIC targets

PE investors do not explicitly use DCF or CAPM-based methods. Given their emphasis on IRR and MOIC, however, it is important to know what IRR and MOIC PE investors target and whether those targets bear any relation to CAPM-based returns.

Panel A of Table 1.8 indicates that PE investors say they target median IRRs of 25%. Smaller PE firms and those with global investment operations tend to target higher IRRs. A rough calculation suggests that this target exceeds a CAPM-based rate. In 2012, long-term Treasury bond rates did not exceed 4%. Axelson, Sorensen, and Strömberg (2013) estimate an average portfolio company equity beta of 2.3. Assuming an equity risk premium of 6%, these suggest a CAPM-based discount rate of less than 18%.

The fact that PE investors target returns exceed CAPM-based discount rates is not surprising. PE investors pay their fees out of gross IRRs. PE limited partners receive their returns net of those fees. In other words, to generate a competitive CAPM-based return net of fees, PE investors must target a greater return gross of fees. Similarly, many PE firms argue that they generate returns in excess of the underlying riskiness of the portfolio. To earn positive excess returns, the PE firms would need to target returns that are higher than the return implied by the CAPM risk of the investment.

We also asked two questions to determine whether PE investors adjusted their target IRR to reflect different risks in different deals. These are presented in Panels B and C of Table 1.8. Panel B indicates that over 85% of PE investors adjust their target IRRs for firm riskiness. While most PE investors explicitly do not use a CAPM-based approach, this adjustment could be consistent with one. Unfortunately, the survey did not explicitly define firm risk. As a result, we cannot distinguish the extent to which firm risk refers to systematic or idiosyncratic risk.

Table 1.8: Internal rate of return target, determinants, and adjustments

			AUM		IRR		Age		Offices	
Variables	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel A: IRR										
Gross IRR target	27.0	25.0	30.0	24.1**	24.5	24.9	24.8	29.3	25.7	28.9
Number of responses	62	62	31	31	24	22	31	31	36	26
Panel B: IRR determinants										
Firm's riskiness	86.2		84.4	87.9	91.7	91.3	90.3	82.4	91.9	78.6
Leverage	47.7		40.6	54.5	58.3	52.2	51.6	44.1	54.1	39.3
Historical return expectations of LPs	30.8		40.6	21.2	20.8	30.4	22.6	38.2	37.8	21.4
Other	9.2		6.3	12.1	8.3	17.4	16.1	2.9	10.8	7.1
Not applicable	4.6		6.3	3.0	0.0	0.0	0.0	8.8	2.7	7.1
Number of responses	65		32	33	24	23	31	34	37	28
Panel C: Adjustments to the cash flows or the IRR										
Risk of unexpected inflation	17.7	0.0	8.2	26.9**	26.0	13.9	21.2	14.5	12.2	25.0
Interest rate risk	25.5	2.0	22.6	28.3	33.5	26.5	26.3	24.8	26.3	24.5
Term structure risk	18.5	0.0	16.6	20.3	14.9	26.9	22.9	14.4	13.5	25.0
GDP or business cycle risk	55.0	50.0	47.8	61.9	63.6	55.7	59.4	51.0	54.2	56.0
Commodity price risk	28.8	21.0	22.8	34.7	35.5	27.1	30.6	27.2	28.0	29.9
Foreign exchange risk	20.2	10.0	15.7	24.5	25.6	16.6	23.5	17.1	12.9	29.8***
Distress risk	13.0	0.0	8.7	17.2	13.8	11.9	17.2	9.1	9.0	18.2
Size	28.6	10.0	31.8	25.5	25.1	25.5	22.9	33.8	31.1	25.3
Market-to-book ratio	7.5	0.0	5.3	9.6	9.3	5.6	7.4	7.6	6.6	8.6
Momentum	11.8	0.0	9.6	13.9	17.0	10.3	18.9	5.4**	12.9	10.4
Illiquidity	20.3	0.0	22.2	18.5	19.8	6.8	15.2	25.0	15.8	26.3
Other	1.4	0.0	2.8	0.0	0.0	0.0	0.0	2.6	2.4	0.0
Number of responses	65	65	32	33	24	23	31	34	37	28

Notes: Panel A reports the target value of gross IRR used by the sample private equity (PE) investors. Panel B describes the variables that the sample PE investors use to adjust their gross IRR target. Panel C reports the fraction of deals for which the sample PE investors adjust cash flows or the IRR to reflect different risks. The sample is divided into subgroups based on the median of assets under management (AUM), the IRR of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. LPs = limited partners; GDP = gross domestic product.

Panel B indicates that less than half of the PE investors adjust their target IRRs for deal leverage. This suggests that the more than half of the PE investors who do not make such an adjustment explicitly do not take a CAPM-based approach.

Panel C reports the fraction of deals that PE investors adjust cash flows or the IRR to reflect different risks. These risks can be divided into macroeconomic or systematic risks (unexpected inflation, interest rate, term structure, business cycle, and foreign exchange) and firm-specific risks (distress, size, market-to-book, momentum, and illiquidity). The results indicate that PE investors are somewhat sensitive to macroeconomic risks, particularly gross domestic product (GDP) or business cycle risk in which PE investors make some adjustment in roughly half of their deals. This is consistent with PE investors taking market or equity risk into account. This is also is suggestive of PE investors having time varying hurdle rates. Firm-specific adjustments appear less important, although some of the PE firms use a variety of firm-specific factors to adjust their target hurdle rates.

Table 1.9: Multiple of invested capital (MOIC)

			AUM		IRR		Age		Offices	
	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Multiple of invested capital	2.85	2.50	3.16	2.54**	2.51	2.56	2.50	3.14**	2.98	2.67
Number of responses	62	62	31	31	24	21	28	34	36	26

Notes: This table measures the value of gross MOIC targeted by the sample private equity (PE) investors. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table 1.9 indicates that PE investors say they target median MOICs of 2.5 times their investment. At a five-year time horizon, this implies a gross IRR of approximately 20%. The mean MOIC of 2.85 times implies a gross IRR of 23%. The MOIC targets, therefore, imply slightly lower gross IRRs than reported gross IRR targets. Smaller and younger private equity firms generally tend to have higher MOIC targets.

1.4.1.6 Net of fee targets (marketed to LPs)

We ask private equity investors not only about the targets they use to evaluate their investments, but also how their limited partners evaluate the performance of the private equity investors. Benchmarking of private equity returns has seen significant evolution in recent years both from an academic and from a data vendor perspective.

Table 1.10: Benchmark for limited partners

		AUM		IRR		Age		Offices	
Benchmark	Mean	Low	High	Low	High	Old	Young	Local	Global
Net IRR	25.4	29.0	21.9	27.3	21.7	26.7	24.2	22.2	29.6
Net IRR versus S&P 500	7.9	6.5	9.4	9.1	4.3	10.0	6.1	8.3	7.4
Net IRR with respect to fund vintage year	27.0	19.4	34.4	27.3	43.5	40.0	15.2**	33.3	18.5
Net multiple or cash-on-cash	38.1	45.2	31.3	31.8	30.4	20.0	54.5***	33.3	44.4
IRR of other GPs	1.6	0.0	3.1	4.5	0.0	3.3	0.0	2.8	0.0
Number of responses	63	31	32	22	23	30	33	36	27

Notes: This table reports the most important benchmark for the LPs investing in the sample private equity (PE) investors. Net indicates net of all fees. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. S&P = Standard & Poor's; GPs = general partners.

Table 1.10 reports the benchmark that the PE investors say is most important for their LPs. Surprisingly, almost two-thirds of the PE investors report that an absolute measure of performance, net IRR and net MOIC, is most important. In less than 8% of the cases do the PE investors believe that LPs view performance relative to public markets as the most important performance benchmark. This is surprising given the large attention paid to alphas and relative performance in public market investments such as mutual funds and hedge funds. An additional 27% believe the performance relative to other PE investors is most important. The only difference among private equity firm types appears to be that older private equity firms' investors evaluate net IRR relative to fund vintage year more frequently and younger private equity firms' investors look to cash-on-cash multiples. Overall, the focus on absolute performance is notable and surprising given the intense focus on relative performance or alphas for public market investments.

In their survey, Da Rin and Phalippou (2014) also find that LPs place a great emphasis on IRRs and MOICs in evaluating PE funds and firms. Unfortunately, Da Rin and Phalippou do not clearly distinguish between relative and absolute performance.

Table 1.11 reports the net IRR that the PE investors market to their LPs. The median net IRR is between 20% and 25%. Consistent with the PE investors' gross IRR targets, this would correspond to a gross IRR of between 25% and 30%. And as with the gross IRR targets, these net IRR targets seem to exceed what one would expect in a CAPM-based framework.

Table 1.11: Net internal rate of return marketed to limited partners

		AUM		IRR		Age		Offices	
Marketed IRR	Mean	Low	High	Low	High	Old	Young	Local	Global
0–5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5–10%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10–15%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15–20%	15.6	18.8	12.5	13.0	13.0	23.3	8.8	18.9	11.1
20–25%	50.0	40.6	59.4	65.2	47.8	53.3	47.1	45.9	55.6
25–30%	23.4	25.0	21.9	21.7	30.4	20.0	26.5	24.3	22.2
$>$ 30%	10.9	15.6	6.3	0.0	8.7	3.3	17.6	10.8	11.1
Number of responses	64	32	32	23	23	30	34	37	27

Notes: This table describes the typical IRR that the sample private equity (PE) investors market to their LPs. The sample is divided into subgroups based on the median of assets under management (AUM), the IRR of most recent fund, the age of PE investor, and by whether PE investor has a global presence.

1.4.1.7 Discussion

These somewhat surprising valuation results raise several potential alternative explanations. First, because private equity is viewed by many limited partners (and marketed as such by some general partners (GPs)) as an absolute return investment, nominal hurdle rates could be more meaningful than discounted cash flow valuation based upon CAPM discount rates. Because underlying portfolio companies were typically only periodically revalued (if at all) in the past, private equity fund returns may not be risk-adjusted by limited partners in a traditional sense. Alternatively, private equity investors may be skeptical of asset pricing models that seek to measure risk. As such, far more of their energy is focused on estimating reasonable cash flows.

Our analysis of the factors that affect private equity firm hurdle rates also indicates a deviation from what is typically recommended in finance research and teaching. It suggests that while PE investors do not use a CAPM-based framework, they do use what appears to be an ad hoc multi-factor framework. Some of the underlying ad hoc factors appear related to systematic risk and others relate to non-systematic risk, i.e., it appears that many private equity firms care about the total risk of the investment when determining the hurdle rates. This would be consistent with the lack of risk-adjusting investment returns on the part of limited partners. If that is the case, then private equity managers would care about adjusting the hurdle rates for both types of risk. Similarly, the diversity of criteria factored into a PE firm's gross IRR target means that unlike a CAPM-based discount rate, which would be the same across different private equity firms, PE firm hurdle rates are likely to vary significantly for similar investments and are likely to be PE firm-, time period-, and portfolio company-specific.

Our results concerning exit multiples being based on comparable companies suggests that PE investors are somewhat skeptical of CAPM-based methods for valuing companies relative to the use of multiples-based approaches. This is at odds with methods taught in basic finance courses in which terminal or exit values are calculated using growing perpetuity formulas with comparable companies' methods possibly used as a check on the CAPM-based approach.

The IRR analysis also embeds the action plan of the private equity firm. Typical holding periods for investments are centered around five years (the typical projection length), and exit values are determined by industry multiples (what they hope to sell the company for at exit). As such, the effort put into the typical IRR model helps private equity firms manage their portfolio more than DCF does. In essence, the framework of investment evaluation can be tied to the investment fund structure that imposes limited holding periods and less transparency on underlying valuation movements, i.e., systematic risk.

1.4.2 Capital structure

As Graham and Harvey (2001), among others, note, a long-standing question in corporate finance is whether firms have a target capital structure that is determined by a trade-off between the costs and benefits of taking on debt. Among the most taught factors that finance educators argue should influence optimal debt levels is the trade-off theory in which managers set debt levels to balance the tax of interest deductibility and disciplining of management with the expected costs of financial distress. The costs of distress include the inability to invest in valuable future projects, retain customers, or retain employees because of cash constraints or questions about long-term viability. In their survey, Graham and Harvey find some support for the trade-off theory (as well as some support for pecking order theory). They also find that CFOs place their greatest focus on retaining financial flexibility and a good credit rating.

AJSW (2013) contrast the trade-off theory of capital structure with a market timing view. From their perspective, the trade-off theory implies that industry factors play an important role in optimal capital structure because industries vary in cash flow volatility (affecting the probability of distress and agency costs) as well as investment opportunities and tangibility (affecting the costs of distress). They argue that buyout firm leverage thus should be related to the leverage of public companies in the same industry. In the market timing view, in contrast, leverage and capital structure respond to economy-wide debt market conditions. When interest rates are low, firms tend to raise more debt. When equity prices are high, firms raise capital by issuing more equity. For a large sample of buyouts, they do not find any support for the trade-off theories. Buyout capital structures are not related to capital structures of similar public companies. Instead, consistent with market timing, leverage is highly related to economy-wide debt market conditions.

1.4.2.1 Survey results

In our survey, we asked the PE investors how they determine the initial capital structure of their portfolio companies. We included both trade-off- and market timing-related factors. Table 1.12 reports the typical capital structure that PE investors target at closing. They target a median debt-to-total capital of 60% and a median debt-to-EBITDA ratio of 4.0 times. Some observers believe these ratios are surprisingly low. They are much lower than the ratios that were common in the 1980s. They also are somewhat lower than the median ratios of 70% and 5.2 times, respectively, in AJSW (2013).

Table 1.12: Capital structure at closing

Capital structure measure	Mean	Median	AUM		IRR		Age		Offices	
			Low	High	Low	High	Old	Young	Local	Global
Debt-to-capital (percent)	55.7	60.0	54.3	57.2	56.6	56.9	55.0	56.4	55.0	56.8
Number of responses	62	62	31	31	22	23	30	32	37	25
Debt-to-EBITDA ratio	3.9	4.0	3.6	4.2**	4.1	4.2	4.2	3.6**	3.8	4.1
Number of responses	60	60	31	29	22	21	29	31	36	24

Notes: This table reports the typical capital structure at closing for the sample private equity (PE) investor portfolio companies measured as debt-to-total capital and debt-to-EBITDA (earnings before interest, taxes, depreciation, and amortization). The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Two likely reasons explain why these survey ratios are lower. First, we conducted our survey in 2012, a year in which debt ratios and debt availability were lower than the historical average. Second, a number of the investors in our survey invest in growth equity as well as buyouts. As their name suggests, growth equity investments are likely to use less leverage than buyouts.

We also find that larger and older private equity investors tend to target more levered capital structures. This is perhaps not surprising given that larger private equity firms target investments in larger companies that can sustain greater leverage.

The survey asks what factors the PE investors consider in determining capital structure. The trade-off theory suggests a role for firm industry, tax benefits, default risk and the ability to generate operating improvements or reduce agency costs. Panels A and B of Table 1.13 present the key results. Panel A reports whether the PE investors consider a particular factor, and Panel B reports the rankings of those factors (where 6 is the top or highest rank). Both Panels A and B suggest that the trade-off theory and market timing are equally important. Almost all of the PE investors consider both industry factors and current interest rates in determining capital structure. These two rank well above the others in importance. Roughly two-thirds of the PE investors explicitly think about the trade-off between tax benefits and default risk, and the same percentage also say they raise as much debt as the market will bear. These factors tie for third in importance. Just under 40% consider the ability of debt to force operational improvements in the manner suggested by Jensen (1989). Finally, only six firms, or less than 10%, mention financial flexibility as an important determinant of capital structure. This contrasts sharply with the strong emphasis on financial flexibility among CFOs in Graham and Harvey (2001).

Table 1.13: Capital structure factors considered important and ranked

			AUM		IRR		Age		Offices	
	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel A: Capital structure factors – important										
Ability of debt to force operational improvements	39.1		31.3	46.9	39.1	30.4	33.3	44.1	29.7	51.9
Use as much debt as the market will allow	65.6		65.6	65.6	65.2	69.6	73.3	58.8	62.2	70.4
Current interest rates and how much the company can pay	95.3		93.8	96.9	95.7	95.7	96.7	94.1	97.3	92.6
Industry that the firm operates in	96.9		93.8	100.0	95.7	95.7	93.3	100.0	97.3	96.3
Maximize trade-off between tax benefits and risk of default	67.2		59.4	75.0	65.2	78.3	66.7	67.6	64.9	70.4
Other	35.9		40.6	31.3	17.4	52.2**	36.7	35.3	43.2	25.9
Number of responses	64		32	32	23	23	30	34	37	27

Table 1.13: Capital structure factors considered important and ranked (Continued)

			AUM		IRR		Age		Offices	
	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel B: Capital structure factors – rank										
Ability of debt to force operational improvements	1.3	0.0	1.1	1.6	1.0	1.2	1.1	1.5	0.9	1.9**
Use as much debt as the market will allow	2.5	3.0	2.5	2.5	2.5	2.7	2.8	2.3	2.5	2.6
Current interest rates and how much the company can pay	5.0	5.0	4.7	5.3	5.1	4.9	5.0	4.9	4.9	5.0
Industry that the firm operates in	4.5	5.0	4.4	4.5	4.7	4.0	4.3	4.6	4.5	4.4
Maximize trade-off between tax benefits and risk of default	2.5	3.0	2.4	2.7	2.7	2.7	2.5	2.6	2.5	2.5
Other	1.8	0.0	2.1	1.4	0.8	2.7**	1.8	1.8	2.1	1.3
Number of responses	64	64	32	32	23	23	30	34	37	27

Notes: Panel A reports the factors that the sample private equity (PE) investors consider in determining how much debt to raise for a transaction. Panel B reports the ranking of factors that the sample PE investors consider important in determining how much debt to raise for a transaction. A higher number means it is a more important factor with 6 being the highest rank. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

1.4.2.2 Discussion

Our market timing result is very consistent with the result in AJSW (2013). Although we did not confirm this explicitly, the result to "use as much debt as the market will allow" also is consistent with the result in AJSW that the availability of leverage affects the pricing of a deal and, possibly, the decision to do one.

Our finding that PE investors do consider trade-off-related factors is not. The question is how can the PE investor and AJSW results be reconciled? One possible explanation is that it is very difficult for outside observers to measure optimal capital structure. It is unlikely that all public companies in the same industry have the same optimal capital structure, and it also is unlikely that all public companies are optimizing. In addition, the companies that PE investors select to invest in are likely to be those that were not optimizing and for whom there is room for improvement. Both of these factors will introduce noise into the tests conducted by Axelson, Jenkinson, Strömberg, and Weisbach.

Another possibility is that the PE investors answered yes to the trade-off theory simply because they consider taxes and financial distress to be important, albeit not explicitly for capital structure. We think this is less likely given the fact that they did rank the trade-off in a tie for third, suggesting it matters.

The fact that most private equity firms do not consider financial flexibility when setting capital structure is potentially explained by the private equity firm's ability to inject capital in the future. Because most private equity firms own the company and have access to inside information, less asymmetric information exists that would create an equity financing constraint. The private equity firms typically have existing funds with undrawn capital and can always invest additional equity. In fact, we often see such follow-on equity investments in situations in which portfolio companies make roll-up acquisitions. In these settings, the typical concern about financial flexibility that was identified in Graham and Harvey (2001) would be less of a concern.

Overall, then, the survey indicates that PE investors consider both trade-off and market timing theories. This is arguably favorable both to the traditional instruction at business schools and to the more recent advances in behavioral finance.

1.4.3 Incentives

Management incentives are supposedly an important piece of financial and governance engineering. Table 1.14 is consistent with this. It confirms previous work by Kaplan (1989), Kaplan and Strömberg (2009), and Acharya, Gottschalg, Hahn, and

Kehoe (2013) that PE investors provide strong incentives to portfolio company management. On average, PE investors allocate 17% of company equity to management and employees. The CEO obtains an average of 8%. The percentages are slightly lower, at 15% and 6%, respectively, for the larger PE investors who invest in larger companies. This is significantly higher than equity ownership of senior management in public companies. For example, Page (2011) finds that the average CEO of a public company between 1993 and 2007 held 3.58% of the company's equity and the median CEO held only 1.57%.

Table 1.14: Typical equity ownership

			AUM		IRR		Age		Offices	
	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
PE investors	79.6	85.0	74.9	84.3**	82.7	83.6	82.9	76.6	81.2	77.3
CEO	8.0	5.0	10.0	6.0	7.1	6.1	7.8	8.2	6.9	9.5
Top ten management (excluding CEO)	7.2	7.0	8.1	6.3**	7.1	6.9	7.0	7.3	7.6	6.6
Other employees	1.8	0.0	1.1	2.4	3.0	0.9	1.7	1.8	1.3	2.5
Other	3.5	0.0	6.0	1.1**	0.1	2.6	0.6	6.1**	3.0	4.3
Number of responses	64	64	32	32	23	23	30	34	37	27

Notes: This table reports the typical equity ownership of the sample private equity (PE) investors, the chief executive officer (CEO), and top management. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

1.5 Governance engineering

In this section, we consider PE investors' attitudes toward corporate governance. First, we consider the structure of the boards of directors of their portfolio companies. Second, we consider their attitudes toward monitoring, hiring, and firing top management.

Panel A of Table 1.15 confirms previous work in showing that PE investors prefer small boards of directors with more than 90% including between five and seven members. Larger private equity firms tend to have portfolio companies with larger boards. Panel B indicates that PE investors take roughly three of the board seats while allocating one or two to management and one or two to outsiders who are not affiliated with the PE firms. Again, the results for board composition are consistent with previous work and with conventional wisdom.

Table 1.15: Board of directors' size and composition

			AUM		IRR		Age		Offices	
	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel A: Board of directors' size										
3 or less	3.1		3.1	3.1	8.7	0.0	3.3	2.9	0.0	7.4
4	1.6		3.1	0.0	0.0	4.3	0.0	2.9	2.7	0.0
5	32.8		40.6	25.0	21.7	30.4	23.3	41.2	37.8	25.9
6	10.9		12.5	9.4	21.7	8.7	20.0	2.9**	10.8	11.1
7	46.9		37.5	56.3	39.1	52.2	46.7	47.1	43.2	51.9
8	3.1		0.0	6.3	8.7	0.0	3.3	2.9	2.7	3.7
9	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	1.6		3.1	0.0	0.0	4.3	3.3	0.0	2.7	0.0
11 or more	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Number of responses	64		32	32	23	23	30	34	37	27
Panel B: Board of directors' composition										
Inside directors	1.6	1.0	1.6	1.5	1.4	1.5	1.5	1.6	1.5	1.7
PE directors	2.8	3.0	2.7	2.9	2.8	2.9	2.8	2.7	2.7	2.8
Outside directors	1.7	2.0	1.6	1.9	1.9	1.7	1.9	1.6	1.8	1.6
Other	0.1	0.0	0.1	0.1	0.0	0.2	0.1	0.1	0.1	0.1
Number of responses	64	64	32	32	23	23	30	34	37	27

Notes: Panel A presents the desired size of board of directors reported by the sample private equity (PE) investors. Panel B presents the desired composition of the board of directors by the sample PE investors. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table 1.16 indicates that PE investors are actively involved in advising their companies in the great majority of their deals. In fact, the median PE investor claims to be actively involved in all of his or her deals. Again, it would be surprising if we found otherwise.

Table 1.16: Private equity involvement in portfolio companies

			AUM		IRR		Age		Offices	
Active involvement	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Percent of deals	87.5	100.0	84.8	90.1	81.3	90.2	85.2	89.5	83.0	93.6
Number of responses	64	64	32	32	23	23	30	34	37	27

Notes: This table reports the fraction of deals in which the sample PE investors become involved in the management of portfolio companies, i.e., actively advising the company on strategic choices. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence.

Tables 1.17 and 1.18 explore how active the PE investors are in recruiting senior management teams in their portfolio companies. Table 1.17 indicates that the majority of PE investors, almost 70%, invest in the existing management team. They do not recruit their own senior management team before the investment. This is consistent with the notion that many private equity firms want to be seen as remaining friendly when pursuing transactions. Management is often critical to successfully executing transactions.

At the same time, however, a meaningful fraction of PE investors, 31%, do recruit their own senior management teams before investing. This suggests that different PE investors have very different investment strategies. It also suggests that the PE investors who bring in their own team do not place a great deal of weight on the value of incumbency.

Table 1.17: Private equity recruitment of management teams

Senior management recruitment	Mean	AUM		IRR		Age		Offices	
		Low	High	Low	High	Old	Young	Local	Global
Before investing									
Yes	31.3	31.3	31.3	26.1	39.1	30.0	32.4	29.7	33.3
No	68.8	68.8	68.8	73.9	60.9	70.0	67.6	70.3	66.7
After investing									
Yes	50.0	40.6	59.4	43.5	52.2	50.0	50.0	37.8	66.7**
No	50.0	59.4	40.6	56.5	47.8	50.0	50.0	62.2	33.3**
Before or after investing									
Yes	57.8	53.1	62.5	47.8	63.4	56.7	58.1	48.6	70.4*
No	42.2	46.9	37.5	52.2	36.6	43.3	41.9	51.4	29.6*
Number of responses	64	32	32	23	23	30	34	37	27

Notes: This table reports the percentage of the sample PE investors who recruit their own senior management teams before investing, after investing, and before or after investing. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table 1.18: Private equity replacement of chief executive officers after investing

CEO replaced	Mean	Median	AUM		IRR		Age		Offices	
			Low	High	Low	High	Old	Young	Local	Global
Percent of deals	33.3	30.0	30.3	36.3	27.9	37.3	27.7	38.2	32.0	35.0
Number of responses	64	64	32	32	23	23	30	34	37	27

Notes: This table reports the percentage of deals in which the sample PE investors replace the CEO after the investment is made. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence.

After the investment, roughly 50% of the PE investors end up recruiting their own senior management team. This is consistent with some of the PE investors becoming more actively involved in the governance of their companies after the investment. When we combine the PE investors who recruit their own teams before, or after, or both before and after investing, we find that almost 58% of the PE investors recruit their own senior teams. Again, this suggests that the PE investors are actively involved in monitoring and governing their portfolio companies.

Although ascribing any causality at this point is not possible, the cross-sectional results suggest that the PE investors who recruit their own teams have experienced better past investment performance. Similarly, larger and global private equity firms are more likely to recruit their own management teams at some point.

1.6 Operational engineering and value creation

In this section, we explore the ways in which the PE investors attempt to create value for their investments and add value to their portfolio companies.

1.6.1 Deal Sourcing

PE investors claim that an important determinant of value creation is the ability to find or source deals that are proprietary in some sense. Accordingly, we asked several questions concerning deal sourcing. Table 1.19 reports the deal funnel experience of our PE investors. For every hundred opportunities considered, the average PE investor deeply investigates 15, signs an agreement with about eight, and closes on fewer than four. This suggests that PE investors devote considerable resources to evaluating transactions despite the fact that they ultimately invest in only a very few. When we compare the deal funnel at different types of private equity firms, larger and older private equity firms pass a greater fraction of their deals through to the next stage. There are three explanations for this result. First, larger and older private equity firms could just have higher quality initial deal sourcing and, hence, do not need to weed out as many deals at all stages. Second, larger firms could have more resources available, so they do not have to eliminate possible deals so quickly. Third, the larger fund sizes could reduce the stringency of the deal funnel. It also appears, without attributing causality, that better performing PE investors are more selective in the deal consideration process.

Table 1.19: Deal funnel

	Mean	Median	AUM		IRR		Age		Offices	
			Low	High	Low	High	Old	Young	Local	Global
All considered opportunities	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Deep due diligence	15.1	12.0	12.7	17.4*	17.6	13.7	16.5	13.9	14.5	15.9
Offer term sheet or negotiate detailed terms	12.9	10.0	11.4	14.4	14.6	12.1	13.2	12.6	12.5	3.4
Sign LOI	8.2	5.0	6.8	9.6	9.0	7.0	8.5	7.9	6.2	10.9**
Close	3.6	3.0	3.0	4.1*	4.1	2.9	3.7	3.5	3.0	4.3*
Number of responses	71	71	35	36	26	26	33	38	41	30

Notes: This table reports the percentage of opportunities considered by the sample private equity (PE) investors that reach different investment stages. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. LOI = letter of intent.

Table 1.20 considers the source and proprietary nature of the deals that the PE investor actually closed. According to the PE investors, almost 36% of their closed deals are proactively self-generated, 7.4% are provided by management, and 8.6% come from their executive network. These arguably have the potential to be proprietary. In contrast, 33% are investment banking generated, 8.6% come from deal brokers, and 4.3% come from other PE firms. These are unlikely to be proprietary. Smaller and younger private equity firms generally tend to source more proprietary deals. This likely reflects smaller target deal sizes. Firms that invest in large and mega deals are less likely to be able to generate proprietary deals given that their targets are probably more likely to be sold in an auction process. Finally, younger private equity firms tend to utilize their executive networks more frequently.

Table 1.20: Deal sources

Deal source	Mean	Median	AUM Low	AUM High	IRR Low	IRR High	Age Old	Age Young	Offices Local	Offices Global
Proactively self-generated	35.6	30.0	37.7	33.5	39.3	35.5	35.8	35.4	35.3	35.9
Investment bank-generated	33.3	25.0	30.5	36.0	33.0	37.0	38.2	29.1	33.0	33.7
Inbound from management	7.4	5.0	5.8	8.9	6.1	9.0	7.4	7.3	7.2	7.6
Other PE firm	4.3	0.0	5.4	3.3	4.1	2.2	4.1	4.5	5.0	3.5
Deal brokers	8.6	0.0	9.5	7.7	6.8	7.1	8.4	8.7	8.7	8.5
Executive network	8.6	5.0	8.3	9.0	8.8	8.5	4.6	12.1***	9.1	8.0
LPs or investors	1.7	0.0	2.5	0.9	0.6	0.7	0.4	2.7	1.2	2.3
Conferences	0.6	0.0	0.3	0.9	1.0	0.3	1.1	0.3	0.5	0.8
Other	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.1	0.0
Percent of closed deals considered proprietary	47.9	50.0	54.0	41.9**	48.0	43.9	41.5	53.4	47.6	48.3
Number of responses	71	71	35	36	26	26	33	38	41	30

Notes: This table reports the percentage of the sample private equity (PE) investors who closed deals they identify from different sources and the percentage of closed deals the sample PE investors consider proprietary. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. LPs = limited partners.

When asked to summarize these sources, the PE investors considered almost 48% of their closed deals to be proprietary in some way. Unfortunately, we have no way of evaluating exactly what proprietary means and we cannot validate the extent to which the deals truly are proprietary or advantaged.

Nevertheless, we think these results indicate that the PE investors explicitly consider the extent to which their potential investments are proprietary and attempt to invest in deals that are.

1.6.2 Deal Selection

To better understand how PE investors select and differentiate among investments, we asked them to rank the factors they considered in choosing their investments where 6 is the highest rank. Table 1.21 reports these results. The most important factor in choosing an investment is the business model or competitive position of the company. The management team, the PE investor's ability to add value, and the valuation are the three next most important factors and are roughly of equal importance. The industry or market of the company and the fit with the PE investor's fund are of least importance.

Table 1.21: Deal selection

			AUM		IRR		Age		Offices	
Deal selection factor	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Ability to add value	3.6	3.0	3.6	3.6	3.9	3.5	3.5	3.7	3.5	3.8
Business model or competitive position	4.6	5.0	4.5	4.7	4.5	4.5	4.4	4.7	4.6	4.5
Fit with fund	2.3	2.0	2.7	1.9	2.0	2.2	2.2	2.4	2.5	2.0
Industry or market	3.2	3.0	3.4	3.0	3.3	3.0	3.3	3.1	3.5	2.8
Management team	3.8	4.0	3.7	4.0	3.9	4.0	4.1	3.6	3.8	3.8
Valuation	3.5	3.0	3.2	3.8	3.4	3.8	3.5	3.5	3.0	4.1***
Number of responses	65	65	32	33	24	23	31	34	37	28

Notes: This table reports the ranking of factors considered by the sample private equity (PE) investors in choosing investments (where 6 is the highest rank). The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Two of these results are notable. First, the PE investors put somewhat more weight on the business than on the management team. This result is consistent with the work of Kaplan, Sensoy, and Strömberg (2009) showing that, at least within the venture capital world, the business strategies of firms remain far more stable (and hence are more important) than the stability of management. Second, the importance of the ability to add value suggests that PE investors take operational engineering and adding value seriously. This also suggests that different private equity firms are likely to target and value investments differently. Private equity firms often have particular industry experience and focus. A successful track record in a particular industry is likely to lead to greater investment focus on a particular sector.

The survey asked the selection question in another way by inquiring about the drivers of return PE investors anticipate when making investments where 6 is, again, the highest rank. Panel A of Table 1.22 reports the percentage of PE investors who view a return driver as important, and Panel B of Table 1.22 reports the ranking of those return drivers.

Table 1.22: Return driver importance and ranking

			AUM		IRR		Age		Offices	
	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel A: Return driver – important										
Growth in the value of the underlying business	100.0		100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Industry-level multiple arbitrage	64.8		74.3	55.6	50.0	65.4	66.7	63.2	61.0	70.0
Leverage	76.1		68.6	83.3	65.4	88.5**	81.8	71.1	73.2	80.0
Operational improvements	97.2		94.3	100.0	100.0	96.2	100.0	94.7	95.1	100.0
Refinancing	36.6		28.6	44.4	34.6	42.3	45.5	28.9	29.3	46.7
Other	26.8		28.6	25.0	23.1	19.2	21.2	31.6	31.7	20.0
Number of responses	71		35	36	26	26	33	38	41	30
Panel B: Return driver – rank										
Growth in the value of the underlying business	5.7	6.0	5.8	5.7	5.9	5.5**	5.7	5.7	5.8	5.6
Industry-level multiple arbitrage	2.4	3.0	2.8	2.1	1.9	2.4	2.3	2.6	2.1	2.9
Leverage	2.6	3.0	2.4	2.8	2.3	3.2	3.0	2.2**	2.5	2.7
Operational improvements	4.6	5.0	4.5	4.7	4.9	4.6	4.7	4.5	4.5	4.7
Refinancing	1.0	0.0	0.8	1.3	0.9	1.3	1.2	0.9	0.9	1.2
Other	1.1	0.0	1.2	1.0	0.7	0.8	0.8	1.3	1.3	0.8
Number of responses	71	71	35	36	26	26	33	38	41	30

Notes: Panel A reports the percentage of the sample private equity (PE) investors who mention different return drivers that they bet on in making investments. Panel B reports the return drivers that the sample PE investors bet on in making investments ranked in order of importance where 6 is the highest rank. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Growth in the value of the underlying business is mentioned as a return driver by 100% of the PE investors and is the highest ranked return driver. Operational improvements are close behind, ranked second and mentioned by 97% of the PE investors. Leverage and industry-level multiple arbitrage—selling at a higher multiple than buying—are mentioned by 76% and 65% but rank well behind growth and operational improvements. These results suggest that PE investors invest with the expectation or hope of growing the value of the business and improving operations. Leverage as well as buying low and selling high are viewed as less important.

Once again, these views can be a reflection of the current private equity environment. Historical leverage ratios (in the 1980s and 1990s) were substantially higher than they are today for the typical private equity deal. Also, the growth in the number of private equity firms and capital under management means that there is likely more competition for deals and, hence, less ability to buy companies at a cheap price.

1.6.3 Value Creation

Given the emphasis on growing the value of the business, our next questions asked the PE investors to identify the sources of that value creation. We asked them to distinguish between expected sources of value creation identified before the deal is closed, pre-deal, and actual sources of value creation, post-deal or after the investment is made.

1.6.3.1 Pre-investment

Table 1.23 lists the pre-investment expected sources of value creation. Each deal has a large number of sources of value. Hence, the total expected sources of value add up to well over 100% indicating that PE investors rely on several sources of value

Table 1.23: Pre-investment (expected) sources of value creation

			AUM		IRR		Age		Offices	
Sources of value	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Reduce costs in general	35.6	27.5	35.8	35.5	37.1	37.3	39.9	32.0	31.0	41.8
Improve IT or information systems	26.1	20.0	30.8	21.6	22.0	23.3	23.9	28.0	26.7	25.3
Introduce shared services	15.6	2.5	16.4	14.9	11.6	18.3	16.9	14.6	14.9	16.6
Increase revenue or improve demand factors	70.3	80.0	77.5	63.5**	75.0	63.5	67.0	73.2	70.6	70.0
Redefine the current business model or strategy	33.8	29.5	27.8	39.5	43.0	29.8	32.1	35.3	32.8	35.2
Change CEO or CFO	30.6	27.5	33.4	28.0	29.2	32.9	30.9	30.4	29.3	32.4
Change senior management team other than CEO and CFO	33.4	30.0	37.3	29.7	32.5	33.1	27.9	38.1	35.4	30.8
Improve corporate governance	47.0	37.0	52.4	41.9	40.1	45.5	39.4	53.5	47.3	46.6
Improve incentives	61.1	73.5	60.7	61.5	58.3	67.0	65.5	57.4	59.0	63.9
Follow-on acquisitions	51.1	50.0	53.9	48.4	52.0	46.9	51.0	51.2	53.2	48.3
Strategic investor	15.6	10.0	16.4	14.8	12.3	14.0	14.4	16.5	15.1	16.2
Facilitate a high-value exit	50.0	43.5	61.0	39.6**	45.6	42.0	40.4	58.1**	53.5	45.4
Purchase at an attractive price (buy low)	44.3	43.0	49.2	39.6	38.2	43.3	40.9	47.1	44.9	43.5
Purchase at an attractive price relative to the industry	46.6	50.0	54.5	39.2**	38.7	47.3	42.9	49.8	50.1	42.0
Other	9.8	0.0	9.4	10.2	0.0	14.3**	9.4	10.1	12.4	6.4
Number of responses	74	74	36	38	27	27	34	40	42	32

Notes: This table describes the percentage of deals that the sample private equity (PE) investors identify having specified pre-deal sources of value. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. IT = information technology; CEO = chief executive officer; CFO = chief financial officer.

Table 1.24: Pre-investment value creators

			AUM		IRR		Age		Offices	
Participants	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Deal team	97.7	100.0	96.9	98.4	97.7	99.2	98.4	97.0	97.9	97.4
Operating partners	45.3	40.5	44.9	45.7	46.9	46.3	40.5	49.4	41.6	50.2
Outside consultants	36.8	26.5	27.9	45.1**	35.0	45.3	42.1	32.2	35.0	39.0
Other	7.2	0.0	8.9	5.5	5.1	5.2	4.1	9.8	8.8	5.0
Number of responses	74	74	36	38	27	27	34	40	42	32

Notes: This table reports the percentage of deals that each specified group actively participates in identifying pre-deal value for the sample private equity (PE) investors. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

creation. The most frequently mentioned source of value is increasing revenue, identified by PE investors as being important in over 70% of their deals. Smaller private equity firms identified increasing revenue more often than larger private equity investors. This is not surprising given that there may be more room to increase revenues for the smaller deals targeted by smaller private equity investors. Follow-on acquisitions are also important in more than 50% of their deals. Reducing costs is identified as being important in only 36% of their deals. Introducing shared services, in which the PE investors help their several portfolio companies aggregate demand for services or supplies to improve their bargaining power with suppliers, is also related to reduced costs and is important in 16% of the deals.

Both increasing sales and reducing costs would fit under operational engineering. If these answers are accurate (see Section 1.7), growth is more important than reducing costs, suggesting a shift in emphasis from the cost cutting and agency cost reduction in the 1980s as emphasized in Jensen (1989). The presence of merger and acquisition activity may have led many firms to be more efficient on the cost side, i.e., there may be less corporate waste today than in the past (Kaplan, 1997).

Private equity investors also expect to create value in roughly one-third of their investments by redefining or changing the company's strategy or business model. In roughly one-third of their investments, they expect to create value by changing the CEO or CFO and by changing other members of the senior management team. All of these also would fit under the rubric of operational engineering. Presumably these actions, if successful, would lead to greater growth, reduced costs, or both. Private equity investors also expect to create value by improving incentives (61%) and improving corporate governance (47%). These would fit under the categories of financial and governance engineering discussed in Sections 1.4 and 1.5.

In slightly under half of their investments, private equity investors expect they are able to buy at attractive prices, both absolutely (44.3%) and relative to the industry (46.6%). In roughly half of their investments, they also expect that they can facilitate a high value exit. This suggests that private equity investors believe they create a meaningful amount of value by being able to buy low and sell high. For smaller and younger private equity firms, the ability to engage in multiple expansion is higher. This may reflect the greater frequency of proprietary deals for these types of private equity firms and the potential to complete transactions at lower valuations. Among practitioners and limited partners, this would usually be considered a type of financial engineering, particularly buying low. From an academic perspective, this is difficult to characterize. It is potentially consistent with taking advantage of asymmetric information, superior bargaining ability, market timing, and an efficient allocation of resources (i.e., selling to the right buyer).

We can say that, overall, the answers indicate that PE investors expect to create value pre-investment from a combination of financial, governance, and operational engineering. Different private equity firms typically express different value drivers. Private equity firms appear to engage in differentiated investment strategies with different sources of expected value creation.

We also asked the PE investors who in their organization is involved in identifying the (pre-investment) sources of value creation. Table 1.24 indicates that deal team members (i.e., the financial partners) are involved in virtually every deal. Perhaps the more interesting result is that operating partners, i.e., those primarily with operating instead of financial experience, are involved in identifying value sources in 45% of the deals. In addition to relying on operating partners, Table 1.24 indicates that the PE investors involve outside consultants in almost 37% of their deals. Smaller and younger private equity firms are less likely to engage outside consultants in their transactions. Overall, then, Table 1.24 suggests that the PE investors have made a meaningful investment in operational engineering although that investment is highly variable across firms.

1.6.3.2 Post-investment

Table 1.25 lists post-investment realized sources of value creation. The third column reports the difference in the mean result for pre- and post-investment for each variable. The same sources identified as important pre-investment remain important post-investment except that many of them increase in importance.

Increased revenue remains important in roughly 70% of the deals. Reduced costs increase in importance, rising to 47% of deals, but remain below increased growth. The use of shared services, redefining the strategy, changing the CEO or CFO, and changing other members of the senior management team also increase by 6% to 14% relative to the pre-deal expected sources of value. If anything, then, operational engineering sources of value appear to be more important post-investment than they are identified as or expected to be pre-investment. Improving incentives and improving corporate governance also remain important sources of value, increasing by 4% and 5%, respectively, relative to pre-investment expectations.

Table 1.25: Post-investment sources of value creation

Sources of value	Mean	Median	Δ from pre-deal	AUM Low	AUM High	IRR Low	IRR High	Age Old	Age Young	Offices Local	Offices Global
Reduce costs in general	47.4	48.5	11.7	46.1	48.5	46.5	51.2	52.1	43.3	40.2	56.8**
Improve IT or information systems	33.5	28.0	7.4	36.4	30.6	29.7	35.3	31.0	35.5	32.8	34.3
Introduce shares services	21.9	10.0	6.3	18.5	25.2	21.9	24.0	23.9	20.3	18.8	26.1
Increase revenue or improve demand factors	69.5	71.0	−0.8	73.9	65.3	70.7	68.8	67.2	71.4	69.4	69.6
Redefine the current business model or strategy	40.1	40.0	6.3	34.2	45.7**	52.1	35.0**	39.3	40.8	39.7	40.7
Change CEO or CFO	42.9	40.0	12.3	40.5	45.3	46.3	43.8	44.1	42.0	40.6	46.0
Change senior management team other than CEO and CFO	47.1	50.0	13.7	46.2	48.0	44.1	52.6	46.7	47.4	48.2	45.7
Improve corporate governance	52.1	50.0	5.1	56.2	48.2	51.0	52.1	49.9	54.0	53.6	50.1
Improve incentives	65.1	71.5	3.9	58.3	71.5	70.3	72.3	72.3	59.0	60.5	71.1
Make follow-on acquisitions	48.1	50.0	−3.0	45.1	50.8	47.8	46.7	50.4	46.1	50.7	44.6
Bring on a strategic investor	13.5	10.0	2.1	14.5	12.5	14.1	10.1	13.3	13.6	15.4	10.9
Facilitate a high-value exit	58.8	60.0	8.8	62.7	55.0	55.6	53.6	55.9	61.2	62.8	53.5
Other	7.1	0.0	7.1	8.3	5.9	0.0	7.1	5.6	8.3	9.1	4.3
Number of responses	74	74	74	36	38	27	27	34	40	42	32

Notes: This table reports the percentage of deals that the sample private equity investors identify as having specified post-deal sources of value and the difference from pre-deal sources of value from Table 23. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. IT = information technology; CEO = chief executive officer; CFO = chief financial officer.

Table 1.26: Post-investment value creators

Participants	Mean	Median	AUM Low	AUM High	IRR Low	IRR High	Age Old	Age Young	Offices Local	Offices Global
Deal team	93.3	100.0	90.6	95.9	93.7	95.6	93.5	93.2	92.1	94.9
Operating partners	51.1	50.0	46.8	55.1	56.2	48.5	45.7	55.6	43.6	60.9
Outside consultants	27.1	21.0	22.0	31.9	26.2	34.0	29.3	25.2	25.2	29.5
Other	8.6	0.0	13.0	4.3	3.7	7.9	5.6	11.1	9.2	7.7
Number of responses	74	74	36	38	27	27	34	40	42	32

Notes: This table reports the percentage of deals that each specified group actively participates in identifying post-deal value. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of private equity (PE) investor, and by whether PE investor has a global presence.

Facilitating a high-value exit also becomes somewhat more important with almost 60% of the PE investors citing this as a post-investment source of value. This could reflect the historical perspective of private equity firms that were able to take more proprietary deals public or sell at a higher valuation.

Post-investment, then, the PE investors continue to claim they create value from a combination of financial, governance, and operational engineering. Overall, the post-investment sources of value they realize are somewhat greater than the sources of value identified pre-deal.

We again asked the PE investors who in their organization is involved in identifying the (post-investment) sources of value creation. Table 1.26 indicates that the participants are similar to those involved pre-investment. Deal team members are involved in virtually every deal. Operating partners are involved in identifying value sources in 51% of the deals, slightly higher than the 45% pre-deal, and consultants are involved in 27%, somewhat less than the 37% pre-deal.

1.6.4 Exit

Our final questions relating to value creation concern the exit strategy of PE investors. Table 1.27 indicates that PE investors expect to exit roughly one-half of their deals through a sale to a strategic buyer, i.e., to an operating company in a similar or related industry. In almost 30% of deals, they expect to sell to a financial buyer, i.e., to another private equity investor. In less than 20% of deals, PE investors expect to exit through an initial public offering (IPO). These percentages are consistent with, in fact almost identical to, the exit results in Strömberg (2008) that 53% of deals with known exits are to strategic buyers, 30% are to financial buyers, and 17% are through IPOs.

Not surprisingly, a significant difference exists between larger and smaller PE investors. Larger PE investors expect to exit through an IPO more than 26% of the time, and smaller PE investors expect to do so less than 11% of the time. For the largest deals, it is less likely that many strategic buyers are large enough to sell to.

Table 1.27: Types of exit

			AUM		IRR		Age		Offices	
Type of exit	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
IPO	18.8	11.7	10.9	26.4***	23.7	18.9	20.6	17.2	12.1	27.7***
Strategic sale	51.0	50.0	57.3	44.8**	46.3	51.4	44.2	56.7**	57.5	42.3***
Financial sale	29.5	30.0	31.8	27.3	29.6	28.1	33.6	26.0	30.4	28.3
Other	0.7	0.0	0.0	1.5	0.5	1.6	1.6	0.0	0.0	1.7
Number of responses	63	63	31	32	22	23	29	34	36	27

Notes: This table reports the fraction of deals the sample private equity (PE) investors target for different types of exit. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. IPO = initial public offering.

Panels A and B of Table 1.28, respectively, the presence and the ranking of factors that PE investors consider in deciding when to exit (where 7 is the highest rank). We are interested in whether private equity firms believe that they can time the exit markets (either IPO or mergers and acquisitions markets) or if exits are driven by firm-specific performance. Achieving the expected operational plan and capital market conditions are the most important and are ranked roughly equally. They are important for more than 90% of the PE investors. As with capital structure decisions, this suggests that PE investors put roughly equal weight on fundamentals and on market timing. Management's opinion, competitive considerations and hitting a return target are the next most important considerations and are ranked roughly equally. They are considered by more than 75% of the PE investors. Considering management's opinion is consistent with a cooperative or advisory relation between PE investors and management. The requirement to hit a return target could indicate an agency problem between the PE investors and their limited partners in which the private equity firm's limited partners cannot adjust investment performance for risk and, hence, the private equity managers maintain nominal return thresholds.

Table 1.28: Exit timing, importance and rank

			AUM		IRR		Age		Offices	
Factors	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Panel A: Exit timing – important										
Achieve operational plan set out to achieve	92.2		90.6	93.8	95.7	91.3	90.0	94.1	91.9	92.6
Capital market conditions	96.9		96.9	96.9	100.0	95.7	100.0	94.1	94.6	100.0
Competitive considerations	76.6		75.0	78.1	69.6	78.3	80.0	73.5	83.8	66.7
Hit IRR or ROI target	79.7		71.9	87.5	91.3	82.6	76.7	82.4	75.7	85.2
LPs pressure to return capital	56.3		46.9	65.6	56.5	56.5	43.3	67.6	48.6	66.7
Management's opinion	85.9		81.3	90.6	87.0	82.6	86.7	85.3	86.5	85.2
Other	14.1		15.6	12.5	13.0	13.0	13.3	14.7	10.8	18.5
Number of responses	64		32	32	23	23	30	34	37	27
Panel B: Exit timing – rank										
Achieve operational plan set out to achieve	5.5	6.0	5.4	5.5	5.8	5.3	5.3	5.6	5.5	5.4
Capital market conditions	5.3	5.5	5.4	5.2	5.3	5.3	5.4	5.2	5.0	5.7
Competitive considerations	3.5	4.0	3.5	3.5	3.2	3.1	3.4	3.5	3.9	2.9
Hit IRR or ROI target	4.0	4.0	3.9	4.2	4.2	4.6	3.8	4.3	3.9	4.3
LPs pressure to return capital	1.8	1.5	1.5	2.0	1.9	1.8	1.4	2.1	1.6	1.9
Management's opinion	3.7	4.0	3.4	4.1	3.8	3.7	4.3	3.2**	3.8	3.7
Other	0.7	0.0	0.7	0.7	0.7	0.7	0.6	0.7	0.5	0.9
Number of responses	64	64	32	32	23	23	30	34	37	27

Notes: Panel A describes the factors the sample private equity (PE) investors consider in deciding on the timing of exit. Panel B describes the ranking of factors the sample PE investors consider in deciding on the timing of exit (where higher rank is more important and 7 is the highest rank). The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. ROI = return on investment; LPs = limited partners.

1.7 Private equity firm organization

Up until this point, the survey questions have asked the PE investors to describe what they do with respect to their portfolio company investments. In this section, we report the answers to questions about the organization of the PE firms themselves with the idea of shedding additional light on how they operate and attempt to create value. Historically, private equity firms were small organizations. Since 2000, private equity firms have grown substantially in terms of both employees and structure. We seek to understand how this growth translates into organizational choices.

Table 1.29: Private equity (PE) firm organization

		AUM		IRR		Age		Offices	
Firm organization	Mean	Low	High	Low	High	Old	Young	Local	Global
Industry	54.4	54.1	54.8	65.5	55.2	64.7	46.7	54.5	54.3
Criteria	11.4	10.8	11.9	13.8	3.4	11.8	11.1	6.8	17.1
Product	16.5	5.4	26.2**	17.2	17.2	29.4	6.7***	2.3	34.3***
Generalist	36.7	40.5	33.3	27.6	34.5	26.5	44.4	43.2	28.6
Other	6.3	2.7	9.5	10.3	6.9	8.8	4.4	2.3	11.4
Number of responses	79	37	42	29	29	34	45	44	35

Notes: This table describes how the sample PE investors say their firm is organized. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

In Table 1.29, we report how the PE firms are organized. The notable result here is that only 37% of the PE investors are organized as generalists. This is very different from the organization of the PE firms in the 1980s when most firms and most individual PE investors were largely generalists. At the same time, more than 50% of the firms are organized by industry. Organization by industry likely carries three advantages: PE investors who specialize in an industry are more likely to be able to find an opportunity in that industry, to be able to evaluate the opportunity when it appears, and to understand whether and how it is possible to add value to that opportunity.

In Table 1.30, we report the percentage of investment professionals in different specializations. A majority of employees in our sample firms are deal professionals. An additional 20% can be considered deal-related because they are involved in deal sourcing and deal execution, bringing to almost 75% the percentage of employees who are deal oriented. At the same time, 8.7% of employees are operating professionals, 1.2% are consulting professionals, 5.7% are shared service professionals, and 0.4% are human resources professionals, for a total of 16% who can be considered exclusively concerned with operational engineering. While this percentage is much lower than the percentage of employees who are deal-oriented, it does indicate that meaningful employee resources are devoted to value creation.

Table 1.30: Private equity (PE) firm investment professionals

			AUM		IRR		Age		Offices	
Professionals by specialization	Mean	Median	Low	High	Low	High	Old	Young	Local	Global
Deal professionals	54.2	50.0	57.7	51.2	55.1	59.2	59.3	50.4	58.7	48.6
Deal sourcing professionals	8.9	1.3	11.5	6.5	9.8	3.5**	6.0	11.1	9.8	7.7
Deal execution professionals	9.6	0.0	10.0	9.2	10.4	4.4	5.8	12.4**	11.5	7.2
Operating professionals	8.7	4.3	8.9	8.4	9.8	6.4	7.2	9.8	7.0	10.7
Consulting professionals	1.2	0.0	1.1	1.2	0.8	0.7	0.9	1.3	1.2	1.1
Shared services professionals	5.7	0.0	3.3	7.8	5.3	7.9	6.2	5.4	3.1	8.9**
Fundraising professionals	3.2	1.2	1.6	4.6***	4.0	2.6	2.9	3.4	1.7	5.1***
HR professionals for portfolio companies	0.4	0.0	0.4	0.3	0.2	0.3	0.2	0.5	0.2	0.6
Capital markets professionals	1.8	0.0	0.9	2.5	1.0	2.7	2.9	0.9	0.3	3.6**
Other	6.5	0.0	4.7	8.1	3.6	12.4	8.6	4.9	6.7	6.3
Number of responses	79	79	37	42	29	29	34	45	44	35

Notes: This table reports the percentage of investment professionals in different specializations in the sample PE investor firms. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. HR = human resources.

Table 1.31 considers the extent to which PE investors make use of other advisers to help with deal sourcing and with value creation. Almost 50% of the PE investors utilize senior advisers, a CEO council, or its equivalent. In general, these advisers provide nonfinancial advice on businesses. Almost 40% of the PE investors have an advisory board of such advisers. When we put these together, almost 66% of the PE investors have an advisory board or utilize senior advisers. The PE investors describe these advisers or executives as helping with deal flow, assisting with investment due diligence, providing industry-specific information, serving on boards post-investment, and advising on operating and managerial issues post-investment. Consistent with the earlier evidence on operational engineering, this suggests that many of the PE investors have made meaningful investments in obtaining operating advice.

Table 1.31: Operational engineering assistance

		AUM		IRR		Age		Offices	
	Mean	Low	High	Low	High	Old	Young	Local	Global
Non-LP advisory board or group of advisors	38.0	32.4	42.9	27.6	48.3	38.2	37.8	47.7	25.7**
Senior advisors or CEO council or equivalent	48.1	35.1	59.5**	51.7	62.1	52.9	44.4	47.7	48.6
Hire strategy consultants to help with operating plans	31.6	18.9	42.9**	41.4	34.5	41.2	24.4	27.3	37.1
Number of responses	79	37	42	29	29	34	45	44	35

Notes: This table reports the percentage of the sample private equity (PE) investors who utilize a non-limited partner advisory board, senior advisors, or a chief executive officer (CEO) council or hire strategy consultants. The sample is divided into subgroups based on the median of assets under management (AUM), the internal rate of return (IRR) of most recent fund, the age of PE investor, and by whether PE investor has a global presence. Statistical significance of the difference between subgroup means at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively. LP = limited partner.

Almost 32% of the PE investors hire strategy consultants to help with operating plans. When we combine these with the senior advisers and CEO councils, we find that 72% of the PE investors employ an advisory board, CEO council, or strategy consultants. Many employ a combination of these. Again, this suggests that many of the

PE investors have made meaningful investments in obtaining operating advice. This is perhaps not surprising given the growth and increased competitiveness within the industry and the expected sources of returns.

1.8 Concerns

In our analyses, we assume that PE investors provide accurate responses. Upon contacting PE firms, we assured them that their responses would be aggregated so that they could not be identified in our analyses. Accordingly, the incentive to report overly positive or otherwise inaccurate responses is arguably low because doing so will not benefit any one individual firm directly. We acknowledge, however, that some PE investors could respond overly positively to some questions in the hope that the PE industry will be cast in a more positive light. In this section, we discuss where we think those incentives and behaviors could affect our results.

Any reporting biases should have a minimal effect on how PE investors report the methods they use to value companies. Whether a PE investor uses net present value or IRR seems uncontroversial. The determinants of target IRR also seem uncontroversial. One area in valuation where some incentive to overstate could exist is on target IRR. PE investors could want their limited partners to believe they are targeting higher IRRs than is the case. The countervailing factor is that if the target IRR is overstated, limited partners ultimately will be disappointed and the ability to continue to raise new (and potentially larger) funds could be reduced.

We also think it unlikely that the PE investors gave biased answers to the questions on capital structure. If anything, one might expect them to understate the extent to which they time the market and use as much leverage as they can.

Inconsistent with this, most of the PE investors claim that debt availability and current interest rates are important considerations.

It also seems unlikely that PE investors have an incentive to give biased answers to the questions concerning incentives and boards. Alternatively, one could argue that they have an incentive to downplay the extent to which they replace incumbent management. To the extent that PE investors need to partner with incumbent management, it would not be in their interest to report that they frequently replace incumbents. Inconsistent with this incentive, the majority of PE investors report that they bring in their own top management at some point.

The section in which PE investors could have an incentive to be overly positive is on value creation. To the extent such investors want their LPs to believe that they have access to proprietary deals, PE investors could overstate the extent to which their deals are proprietary. Consistent with this, our PE investors do say that roughly 50% of their investments are proprietary in some way. We do not have any way to evaluate the extent to which this is true. At the same time, however, proprietary deal sourcing suggests that PE investors are able to buy low. One could expect PE investors to have an incentive not to say they can buy low because it does not reflect operating value creation on the part of the PE investors. In fact, the PE investors do identify buying low and selling high as an important source of value.

To the extent that PE investors want to be known for growing their investments (and creating jobs) instead of reducing costs (and cutting jobs), they would have an incentive to overstate the extent to which they rely on growth and understate cost cutting. The result that PE investors identify increasing revenue as the most important source of value both pre- and post-investment is potentially consistent with this. On the other hand, the fact that PE investors identify reducing costs as more important post-investment than pre-investment is less consistent with understating cost cutting. Again, a countervailing force here is that limited partners expect to see growth and look for that value creation.

Overall, then, while the PE investors may have some incentives to shade their survey answers in some areas, particularly regarding deal sourcing and growth, the answers they provided do not give us strong reasons to believe that they acted consistently on those incentives.

1.9 Firm types

The previous sections of this paper examined private equity investor practices in financial, governance, and operational engineering. The analyses consider each practice separately. In this section, we examine the extent to which certain practices are correlated across GPs. In doing so, we attempt to measure whether we can classify different groups of GPs as having different strategies. Our approach is to use the grouping of answers for a given private equity firm to extract types through cluster and factor analyses. We then examine how these types map into our notion of operational, financial, and governance engineering. Finally, we look for variation in firm founder backgrounds and how the types are influenced by the career histories of the individuals who started the various private equity organizations.

1.9.1 Variables

In this subsection, we create a variety of variables that help identify GP practices using measures that embody financial, governance, and operational engineering. To capture difference in investment selection methods, we create a variable that equals one if the GP's primary deal evaluation measure is IRR. We create a measure of proprietary deal sourcing that sums the fraction of deals that GPs say are self-generated, inbound from management, and from their executive network.

We create four capital structure and financial engineering variables that help us characterize the various private equity firms. *CSTIME*, a variable that measures market timing behavior, is calculated as the sum of the rankings GPs give to timing factors—"use as much debt as the market will allow" and "current interest rates and how much the company can pay"—as important determinants of capital structure. Similarly, *CSTRADE* measures capital structure trade-off behavior. It equals the sum of a private equity firm's rankings for "maximize trade-off between tax benefits and risk of default" and "industry that the firm operates in" as important determinants of capital structure. We also create two variables that measure the overall targeted debt levels that the private equity firms say they typically employ. *DTCAP* is simply the typical debt-to-total capital ratio that the private equity manager states they seek, and *DTEB* measures the typical debt-to-EBITDA ratio.

Two variables measure management change that private equity managers engage in both before and after the investment. *RECRUITB* equals one if the GP typically recruits its own senior management team before investing. *RECRUITBA* equals one if the GP recruits its own senior management team before or after investing.

The next set of variables is associated with sources of value that private equity firms say they identify or look to provide. *COSTRED* measures the fraction of deals for which the GP expects prospective cost reductions prior to the investment to be an important source of value. *REVGROW* measures the fraction of deals for which the GP expects prospective revenue growth prior to the investment to be an important source of value. *CHCEO* is the fraction of deals for which the GP expects that changing the CEO to be an important source of value prior to the investment. *BUYLOWSELLHI* is a measure of the general partners' belief that they can create value prospectively by purchasing a company at a low price. The variable is calculated as the sum of the fraction of deals a GP expects that buying low, buying low relative to the industry, or facilitating a high-value exit are important sources of value. *OPPART* is simply the fraction of deals that involve operating partners. *PROPDEAL* is the fraction of deals the PE investors claim are proprietary.

We also create variables that measure the factors that GPs find most important in an investment decision. *INVBUS* is the sum of the ranks given to the business model and the industry in an investment decision. *INVMGMT* is the rank given to the management team. *INVADDV* is the rank given to the ability to add value.

Related to these, we create variables that measure the return drivers on which GPs bet. *GROWTH* equals one if the GP's top ranking is growth in the value of the business. *OPIMP* equals one if the GP's top ranking is operating improvements. *MULTARB* equals one if the GP's top ranking is industry level multiple arbitrage.

Some univariate correlations are worth noting (although they are not reported in a table). High debt to total capital and high debt to EBITDA are positively correlated with capital structure timing, cost reductions, and multiple arbitrage and negatively correlated with proprietary deals, revenue growth, and investing in management. Investing in adding value is positively correlated with operating improvements, cost reductions, operating partners, and changing CEOs, but negatively correlated with investing in management. Recruiting a CEO beforehand is correlated with proprietary deals, revenue growth, and buying low and selling high. Finally, proprietary deals use less debt, less market timing, less cost reduction, and more growth.

1.9.2 Cluster analysis

We first use cluster analysis to divide the firms into groups that allow us to explore how different firm characteristics co-vary. Cluster analysis groups respondents in such a way that the private equity firms within a given cluster are more similar to each other than they are to private equity firms in other clusters. We use partition clustering, which divides "the observations into a distinct number of non-overlapping groups" (kmeans in Stata). We restrict the sample to the 58 firms with complete data responses. We report our results with three clusters. The results are qualitatively similar with four or five clusters.

Table 1.32 reports the results. The second cluster is characterized in terms of our notions of operational, financial, and governance engineering. The firms in this cluster are more likely to say they choose capital structure using trade-off considerations, are more likely to recruit an outside CEO or change the CEO, are more likely to focus on operating improvements including cost reductions and revenue growth, and are more likely to use operating partners. Many of these differences are statistically significant (in univariate tests) between Clusters 1 and 2. In sum, Cluster 2 firms seem to say that they focus more heavily on implementing operating improvements and bringing in new management.

Cluster 1 includes firms that say they engage in the most financial engineering and least operational engineering. They are less likely to use capital structure trade-offs; less likely to mention adding value, operating improvements, cost reductions, and

Table 1.32: Cluster analysis

	Cluster #1		Cluster #2		Cluster #3		All	
Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median
dtcap	0.54	0.60	0.59	0.60	0.54	0.60	0.55	0.60
dteb	3.64	3.50	3.95	4.00	4.11	4.00	3.88	4.00
cstime	7.87	9.00	7.69	8.00	7.32	8.00	7.64	8.00
cstrade	3.48	3.00	5.00	5.00	3.58	4.00	3.93	4.00
invbus	7.83	8.00	7.38	7.50	8.47	8.00	7.91	8.00
invmgmt	4.04	4.00	3.75	3.50	3.79	4.00	3.88	4.00
invaddv	3.04	3.00	4.00	4.00	3.79	4.00	3.55	3.00
recruitb	0.30	0.00	0.44	0.00	0.26	0.00	0.33	0.00
propdeal	0.50	0.50	0.46	0.50	0.53	0.50	0.50	0.50
growth	0.91	1.00	0.63	1.00	0.84	1.00	0.81	1.00
opimp	0.04	0.00	0.25	0.00	0.16	0.00	0.14	0.00
costred	25.17	20.00	55.38	55.50	31.42	20.00	35.55	25.00
revgrow	73.04	80.00	82.19	87.50	66.16	70.00	73.31	80.00
chceo	31.39	29.00	40.06	40.50	30.00	26.00	33.33	30.00
buylowsellhi	181.48	175.00	190.38	190.00	68.74	70.00	147.00	150.00
multarb	3.20	3.00	2.70	3.00	2.60	2.50	2.90	2.50
oppart	13.35	6.00	91.56	100.00	55.05	60.00	48.59	39.50
aum	7.15	2.11	9.11	1.80	12.25	8.00	9.36	2.65
Number of firms	23	23	16	16	19	19	58	58

Notes: This table reports the results of a cluster analysis using partition clustering that divides “the observations into a distinct number of non-overlapping groups” (kmeans in Stata). The analysis generates three clusters. dtcap is debt to total capital; dteb is debt to EBITDA (earnings before interest, taxes, depreciation, and amortization); cstime is the sum of the rankings the private equity (PE) investors give to timing factors as important determinants of capital structure; cstrade is the sum of the rankings given to trade-off factors as important determinants of capital structure; invbus is the sum of the ranks given to the business model and the industry in an investment decision; invmgmt is the rank given to the management team; invaddv is the rank given to the ability to add value; recruitb is one if the PE investor typically recruits its own senior management team before investing; propdeal is the fraction of deals the PE investors claim are proprietary; growth equals one if the PE investor’s top ranking is growth in the value of the business; opimp equals one if the top ranking is operating improvements; costred is the fraction of deals the PE investor expects for cost reductions pre-investment; revgrow is the fraction of deals the PE investor expects for prospective revenue growth pre-investment; chceo is the fraction of deals the PE investor expects that changing the CEO is important pre-investment; buylowsellhi measures the importance of creating value buying low or selling high; multarb equals one if the general partner’s top ranking is industry-level multiple arbitrage; oppart is the fraction of deals that involve operating partners; and aum is assets under management.

operating partners; and are more likely to buy low and sell high. The firms in this cluster also tend to be smaller than those in the other two clusters. Firms in the first cluster also tend to give their management teams a larger equity stake in the business. The third cluster is intermediate between the first two on financial and operational engineering.

1.9.3 Factor analysis

As an alternative to cluster analysis, we use factor analysis to extract the main dimensions of variation in the characteristics of our sample firms. In factor analysis, one seeks to identify correlations among observed variables in terms of underlying unobserved factors of a smaller dimension. Essentially, factor analysis models the observed variables as a function of the unobserved factors.

Table 1.33 reports the factor loadings for the first six factors. The first three factors explain almost two-thirds of the variance in the data and have natural interpretations. The first factor has positive loadings on debt levels, operating improvements, cost reductions, operating partners, and adding value and negative loadings on growth, revenue growth, proprietary deal, and investing in the business. As with the cluster analysis, this suggests that some firms focus on operating improvements while others focus on buying good businesses in which they have some proprietary sourcing advantage. The second factor has its highest positive loadings on changing the CEO and recruiting a CEO before the deal closes and negative loadings on investing in management and operating improvements. This suggests a strong tendency for firms to differ in the extent to which they invest in new management versus incumbent. The

Table 1.33: Factor analysis

Panel A: Principal factors, unrotated (58 observations, 11 retained factors, 143 parameters)

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor #1	2.5695	0.6027	0.2659	0.2659
Factor #2	1.9668	0.2159	0.2035	0.4695
Factor #3	1.7509	0.4964	0.1812	0.6507
Factor #4	1.2545	0.1910	0.1298	0.7805
Factor #5	1.0635	0.3087	0.1101	0.8905
Factor #6	0.7548	0.2473	0.0781	0.9687

Panel B: Factor loadings

Variable	Factor #1	Factor #2	Factor #3	Factor #4	Factor #5	Factor #6
dtcap	0.5621	−0.0327	0.4938	0.0708	−0.2085	−0.2560
dteb	0.5035	−0.0410	0.6676	−0.0047	−0.1817	0.0605
cstime	0.1665	−0.2789	0.3737	0.2625	0.2806	−0.1203
cstrade	0.1097	0.0423	−0.1426	0.1490	−0.0639	0.1176
invbus	−0.2527	0.1049	0.0168	0.3620	−0.5344	−0.1266
invmgmt	−0.2061	−0.2732	0.1520	−0.1401	0.5712	0.1638
invaddv	0.5915	0.0930	−0.2394	−0.3619	−0.1367	0.1696
recruitb	0.1495	0.5952	0.1109	0.2706	0.1373	0.0994
propdeal	−0.3721	0.4450	−0.1385	0.2428	−0.0297	0.3292
growth	−0.6203	0.3045	0.4265	−0.4185	−0.1212	−0.0479
opimp	0.5183	−0.3698	−0.5246	0.3405	−0.0026	0.0244
costred	0.5507	0.1235	0.0199	−0.3660	0.1529	−0.1378
revgrow	−0.0509	0.5792	−0.1024	−0.1207	0.1880	−0.2658
chceo	0.3892	0.6732	−0.2110	−0.0282	−0.0566	−0.0677
buylowsellhi	0.0983	0.3450	0.0160	0.2469	0.3541	−0.2450
multarb	0.2566	0.2428	0.1569	0.3298	0.2231	0.1216
oppart	0.3305	0.0754	−0.2566	−0.3633	−0.0318	0.1694
aum	0.2185	0.1442	0.4313	0.0482	−0.0320	0.5167

Notes: This table reports the results of a factor analysis of sample private equity (PE) firm characteristics and answers. dtcap is debt to total capital; dteb is debt to EBITDA (earnings before interest, taxes, depreciation, and amortization); cstime is the sum of the rankings the PE investors give to timing factors as important determinants of capital structure; cstrade is the sum of the rankings given to trade-off factors as important determinants of capital structure; invbus is the sum of the ranks given to the business model and the industry in an investment decision; invmgmt is the rank given to the management team; invaddv is the rank given to the ability to add value; recruitb is one if the PE investor typically recruits its own senior management team before investing; propdeal is the fraction of deals the PE investors claim are proprietary; growth equals one if the PE investor's top ranking is growth in the value of the business; opimp equals one if the top ranking is operating improvements; costred is the fraction of deals the PE investor expects for cost reductions pre-investment; revgrow is the fraction of deals the PE investor expects for prospective revenue growth pre-investment; chceo is the fraction of deals the PE investor expects that changing the CEO is important pre-investment; buylowsellhi measures the importance of creating value buying low or selling high; multarb equals one if the general partner's top ranking is industry-level multiple arbitrage; oppart is the fraction of deals that involve operating partners; and aum is assets under management. Likelihood-ratio test: independent vs. saturated: chi2(153) = 376.57; p-value = 0.0000.

third factor has high positive loadings on debt levels, capital structure timing, and assets under management and negative loadings on adding value and operating improvements. This suggests a factor that is operating improvements versus financial engineering.

Both the cluster analysis and the factor analysis appear to divide firms into those that have a focus on operating improvements versus financial engineering and those that have a focus on investing in new management versus the incumbent. These results provide one expected and one unexpected result. We do not find it surprising that private equity firms pursue strategies that are largely based on financial engineering and others pursue strategies based on operational engineering. The different firm strategies toward incumbent management, however, are surprising. The importance of people and incentive alignment has been well established within the private equity industry. What has not been explored are the distinctive approaches to solving these people issues. Future research should explore the effectiveness of these various approaches.

1.10 Founder types and firm types

In this section, we consider whether PE firm strategies are related to the characteristics of the founding general partners. We classify the founding general partners of each of the PE firms in our sample. In our sample of firms, we gather information on the identity of firm founders from the private firms' Web pages or news articles. Education and career histories are then gathered from the same sources or via LinkedIn.

A founding general partner is classified as "financial" if the GP worked in investment banking, commercial banking, or investment management or had previously been a chief financial officer. "Operational" GPs are those founders that had prior work history in consulting, operations, or general management. Finally, we classify a founding general partner as having a "private equity" background if the GP came from another PE or venture capital firm prior to founding the current one. For each firm, we calculate the average background of the firm by simply classifying the fraction of founders with each type of career history. We then perform a cluster analysis on those three variables (fraction of each career history) and classify 27 firms as having a finance background, 25 firms as having an operational background, and nine firms as having a private equity background.

In Table 1.34, we explore how these types relate to specific strategies. Private equity firms founded by financial general partners appear more likely to favor financial engineering and investing with current management. Private equity firms that have founders with private equity experience appear to be the most strongly engaged in operational engineering. They are more likely to invest with the intention of adding value, to invest in the business, to look for operating improvements, to change the CEO after the deal, and to reduce costs. Firms founded by general partners with operational backgrounds have investment strategies that fall in between the other two groups.

These results, while preliminary, do seem to indicate that career histories of firm founders have persistent effects on private equity firm strategy. This result is similar to the work of Bertrand and Schoar (2003) that demonstrates persistent effects of senior management in organizations they lead in terms of firm strategy. The strategies identified for private equity firms clearly align with the firm founders' careers. While these results are preliminary, future research should explore whether investments that align with the strength of the firm founders do better or worse in the long run than do investments that deviate from these strengths.

Table 1.34: Relation of founder and firm characteristics

Variable	Mean (all)	Finance	Operations	Other PE
dtcap	0.56	0.52	0.58	0.57
cstime	7.47	7.33	7.76	7.00
cstrade	3.86	3.26	4.64	3.22
invbus	7.77	7.44	8.20	8.56
invmgmt	3.82	4.26	3.56	2.89
invaddv	3.63	3.37	3.52	4.22
recruitb	0.31	0.30	0.32	0.22
propdeal	0.51	0.54	0.46	0.47
growth	0.80	0.78	0.80	0.78
opimp	0.13	0.11	0.12	0.22
costred	35.6	25.0	38.1	42.3
revgrow	70.3	66.6	70.5	80.6
chceo	30.6	26.3	30.4	48.8
buylowsellhi	140.9	155.4	150.2	125.0
aum	9.55	10.30	11.06	4.72
year_founded	1993.5	1992.7	1994.5	1994.2
Number of responses	79	27	25	9

Notes: This table reports the relation of founder characteristics to firm characteristics of the sample private equity (PE) investors. PE investors are classified as finance, operational, or other PE based on a cluster analysis on the fraction of their founders with financial, operational, or previous PE backgrounds. dtcap is debt to total capital; cstime is the sum of the rankings the PE investors give to timing factors as important determinants of capital structure; cstrade is the sum of the rankings given to trade-off factors as important determinants of capital structure; invbus is the sum of the ranks given to the business model and the industry in an investment decision; invmgmt is the rank given to the management team; invaddv is the rank given to the ability to add value; recruitb is one if the PE investor typically recruits its own senior management team before investing; propdeal is the fraction of deals the PE investors claim are proprietary; growth equals one if the PE investor's top ranking is growth in the value of the business; opimp equals one if the top ranking is operating improvements; costred is the fraction of deals the PE investor expects for cost reductions pre-investment; revgrow is the fraction of deals the PE investor expects for prospective revenue growth pre-investment; chceo is the fraction of deals the PE investor expects that changing the chief executive officer is important pre-investment; buylowsellhi measures the importance of creating value buying low or selling high; and aum is assets under management.

1.11 Conclusion

Over the past decade, academic finance has explored the impact of PE firms in a number of areas by examining sometimes limited data. In this paper, we attempt to highlight the impact of PE investors utilizing different data. We report what PE investors say they do by tabulating the results of a survey of PE investing practices. Because PE investors are highly educated, have strong incentives to maximize value, and have been very successful, their practices likely also have been successful. We are interested in how many of their responses correlate with what academic finance endorses and what it teaches. Do private equity investors do what the academy says are best practices?

We find that very few investors use DCF or net present value techniques to evaluate investments, contrary to what one might expect. Instead, they rely on internal rates of return and multiples of invested capital. This contrasts with the results in Graham and Harvey (2001), who find that CFOs use net present values as often as internal rates of return. The result also conflicts with the focus on net present value in most business school finance courses. Furthermore, few PE investors use the capital asset price model to determine a cost of capital. Instead, PE investors typically target a return on their investments well above a CAPM-based rate. Target IRRs also seem to be adjusted by different PE firms utilizing different factors. Hence, different PE firms likely have different target IRRs for the same deals.

The fact that they do not use DCF techniques is interesting. It could indicate that IRR and MOIC techniques are sufficiently robust or effective that DCF techniques are not necessary. Alternatively, it could indicate some practical deficiency with DCF techniques, especially in the private equity setting in which fund structures limit investment horizons and considerable asymmetric information exists between general and limited partners. These settings may make managing via IRR-based investment decisions better.

The fact that PE investors target returns that exceed CAPM-based returns is consistent with their believing that they add meaningful value to their investments and that they need to do so to generate their compensation. As the industry becomes more competitive, it will be interesting to see if target hurdle rates come down.

We also find that PE investors believe that absolute, not relative, performance is most important to their LP investors. The focus on absolute performance is notable given the intense focus on relative performance or alphas for public market investments. There are two possible explanations for this. First, LPs, particularly pension funds, may focus on absolute returns because their liabilities are absolute. Alternatively, the chief investment officers of the LPs choose a private equity allocation based on relative performance, but the professionals who make the investment decisions care about absolute performance or performance relative to other PE firms. We believe that the advent of greater dissemination of risk-based performance benchmarks such as PMEs is likely to affect the view of limited partners and potentially trickle back down to the private equity general partners.

In choosing the capital structures for their portfolio companies, PE investors appear to rely equally on factors that are consistent with capital structure trade-off and market timing theories. Again, these results are somewhat different from those for CFOs in Graham and Harvey (2001). The market timing result is consistent with the findings in AJSW (2013). This result is arguably favorable both to the traditional instruction at business schools and to the more recent advances in behavioral finance.

PE investors expect to provide strong equity incentives to their management teams and believe those incentives are very important. They also structure smaller board of investors with a mix of insiders, PE investors, and outsiders.

Finally, PE investors say they place a heavy emphasis on adding value to their portfolio companies, both before and after they invest. The sources of that added value, in order of importance, are increasing revenue, improving incentives and governance, facilitating a high-value exit or sale, making additional acquisitions, replacing management, and reducing costs. Consistent with adding operational value, the PE investors make meaningful investments in employees and advisers who provide advice and help in implementing operating improvements.

While we recognize that it is possible that some PE investors report overly positively on some questions in the hope that the PE industry will be cast in a more positive light, particularly in aspects of deal sourcing and value creation, the answers they provided do not give us strong reasons to believe that they have a meaningful impact on our findings and conclusions.

We finish with exploratory analyses to consider how financial, governance, and operational engineering practices co-vary within PE firms. The analyses suggest that different firms take very different strategies. For example, some focus much more heavily on operational engineering, while others rely heavily on replacing incumbent management. These investment strategies are strongly influenced by the career histories of the private equity firm founders. It will be interesting (and, with these data, possible) to see which of these strategies, if any, exhibit superior performance in the future.

Chapter 2

The Agglomeration of Bankruptcy[1]

2.1 Introduction

How does bankruptcy spread? While research on bankruptcy and financial distress has documented how bankruptcy reorganizations affect firms that file for Chapter-11 themselves, there is limited evidence on the effect of bankruptcies and financial distress on competitors and industry peers. In this paper, we identify a new channel by which bankrupt firms impose negative externalities on their non-bankrupt competitors, namely, through their impact on peer firm sales and on the propensity to close stores.

Research in industrial organization has argued that the geographic concentration of stores and the existence of clusters of stores can be explained by consumers' imperfect information and their need to search the market (Wolinsky 1983). Indeed, both practitioners and academics argue that economies of agglomeration exist in retail since some stores—those of national name-brands or anchor department stores, in particular—draw customer traffic not only to their own stores but also to nearby stores. As a result, store level sales may depend on the sales of neighboring stores for reasons that are unrelated to local economic conditions (Gould and Pashigian 1998; Gould, Pashigian, and Prendergast 2005).

[1] Co-authored with Efraim Benmelech, Nittai Bergman, and Anna Milanez.

We conjecture that the externalities that exist between neighboring stores, and the economies of agglomeration they create, can be detrimental during downturns, propagating and amplifying the negative effects of financial distress and bankruptcies among firms in the same locality. Our main prediction is that, due to agglomeration economies, retail stores in distress impose negative externalities on their neighboring peers: store sales tend to decrease with the reduction in sales, and ultimately the closure, of neighboring stores. If such negative externalities are sufficiently strong, bankruptcies, and the store closure they involve, will lead to additional store closures and bankruptcies, propagating within a given area.

Identifying a causal link, however, from the bankruptcy and financial distress of one retailer to the sales and closure decisions of its neighboring retailers is made difficult by the fact that bankruptcy filings and financial distress are correlated with local economic conditions. Correlation in sales among stores in the same vicinity may therefore simply reflect weak demand in an area. Similarly, the fact that store closures tend to cluster locally may often be the outcome of underlying difficulties in the local economy, rather than the effect of negative externalities among stores. Local economic conditions will naturally drive a correlation in outcomes among stores located in the same area.

Using a novel and detailed dataset of all national chain store locations and closures across the United States from 2005 to 2010, we provide empirical evidence that supports the view that bankruptcies of retail companies impose negative externalities on neighboring stores owned by solvent companies. Our identification strategy consists of analyzing the effect of Chapter 11 bankruptcies of large national retailers, such as Circuit City and Linens ‘n Things, who liquidated their entire store chain during the sample period. Using Chapter 11 bankruptcies of national retailers alleviates the concern that local economic conditions led to the demise of the company: it is unlikely that a large retail chain will suffer major financial difficulties because of a localized economic downturn in one of its many locations. Supporting this identification assumption, we show that stores of retail chains that eventually end up in Chapter 11 bankruptcy are not located in areas that are worse than the location of stores operated by chains that do not end up in bankruptcy, along a host of economic characteristics.

We then show that stores located in proximity to stores of national chains that are liquidated are more likely to close themselves. Importantly, we find that this effect is stronger for stores in the same industry of the liquidating national chain as compared to stores in industries different from that of the liquidating chain. For example, focusing on stores located in the same address (usually mall locations), the probability that a store will close in the year following the closure of a store belonging to a liquidating national chain is approximately two times larger when operating in the same industry as compared to when the stores operate in different industries.

Finally, we study the interaction between the geographical effect of store closures and the financial health of solvent owners of neighboring stores. We hypothesize that the impact of national chain store liquidations will be stronger on firms in weaker financial health, as these stores are expected to suffer more from the reduction in customer traffic. Focusing on stores owned by a parent company, and measuring financial health using the profitability of the parent, we find that, consistent with our hypothesis, the geographical effect of store closures on neighboring stores is indeed more pronounced in financially weaker firms. For example, when located within a 50 meter radius of a closing national chain store, stores belonging to parent firms in the 25th percentile of profitability are between 16.9 and 22.2 percent more likely to close. In contrast, if the parent firm is in the 75th percentile of profitability there is no statistical significant effect on the likelihood of store closure.

Along the same lines, we also find that larger stores are more resilient to the closure of neighboring stores, exhibiting a lower likelihood of closure following the closure of neighboring stores.

Our paper is closely related to a large body of work on agglomeration economies that studies how the proximity of firms and individuals in urban areas increases productivity. Prior work has shown that increases in productivity can arise for a variety of reasons, including reduced transport costs of goods, increased ability of labor specialization , better matching quality of workers to firms, and knowledge spillovers.[2] Within the retail sector, agglomeration economies may arise because of the increased productivity stemming from reduced consumer search costs. By utilizing micro-level data on store locations and closures our paper contributes in two ways to this important literature.

The first contribution is our focus on the way in which downturns and bankruptcies damage economies of agglomeration and the productivity enhancements they create. In contrast, prior work has focused on the creation of agglomeration economies through firm entry and employment decisions (See, for example, Ellison and Glaeser (1997), Glaeser et al (1992), Henderson et al. (1995), and Rosenthal and Strange (2003)). By focusing on downturns, our work shows how agglomeration economies can be understood to propagate bankruptcies and financial distress. Indeed, firm closures

[2] Important contributions include Krugman (1991a) and (1991b), Becker and Murphy (1992), Helsley and Strange (1990), and Marshall (1920)).

will naturally reduce proximity between agents in an urban environment, which will tend to reduce the productivity of remaining firms due to dis-economies of agglomeration. To the extent that replacing closed stores with new ones takes time—for example due to credit constraints during downturns—the reduction in productivity may have long term consequences.[3]

The second contribution of the paper is the empirical identification of agglomeration economies. The standard difficulty in identifying agglomeration effects is the endogeneity of firms' location decisions. Namely, is firm proximity causing high productivity or, alternatively, is the proximity simply a by-product of firms choosing to locate in areas naturally pre-disposed to high productivity? Employing micro-level data on store locations, we address the endogeneity concern by instrumenting for variation in store location with our large retail-chain bankruptcy instrument.[4] As described above, to the extent that national chain store closures are not driven by highly localized demand-side effects, we can measure the impact of store closures on nearby stores. Agglomeration effects, and the degree to which they attenuate with distance to other stores, are therefore estimated at a micro level.

Our paper also adds to the growing literature in finance on the importance of peer effects and networks for capital structure (Leary and Roberts 2014), acquisitions and managerial compensation (Shue 2013), entrepreneurship (Lerner and Malmendier

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[3] There have been few studies analyzing how firms in bankruptcy or financial distress affect their industry peers. One exception is Benmelech and Bergman (2011) who use data from the airline industry to examine how firms in financial distress impose negative externalities on their industry peers by increasing their cost of debt capital.

[4] Rosenthal and Strange (2008) instrument for the location of firms with the presence of bedrock. Other efforts to deal with the endogeneity concern involve analyzing co-agglomeration effects (see, for example, Ellison et al. (2010)).

2013) and portfolio selection and investment (Cohen, Frazzini, and Malloy 2008). In particular, our paper is closely related to Almazan, De Motta, Titman, and Uysal (2010) who link financial structure to economies of agglomeration. In particular, Almazan, De Motta, Titman, and Uysal (2010) show that firms that are located in industry clusters are more likely to maintain financial slack in order to facilitate acquisitions within these clusters.

The rest of the paper is organized as follows. Section 2.2 explains our identification strategy. Section 2.3 describes our data sources and provides summary statistics and Section 2.4 describes the initial location of stores in our sample. Section 2.5 presents the empirical analysis of the relation between bankrupt store and neighboring store closures. Section 2.6 analyzes the effects of store size and firm profitability on store closures. Section 2.7 concludes.

2.2 Identification strategy

Our main prediction is that, due to economics of agglomeration, the closure of retail stores imposes negative externalities on their neighbors—that is, store sales tend to decrease with a decline in customer traffic in their area. If this effect is sufficiently large, store closures will tend to propagate geographically. However, identifying a causal link from the financial distress or bankruptcy of retailers to the decision of a neighboring solvent retailer to close its stores is difficult because financial distress is potentially correlated with underlying local economic conditions. For example, the fact that local retailers are in financial distress can convey information about weak local demand. Similarly, the fact that store closures tend to cluster locally does not imply in and of itself a causal link but rather may simply reflect difficulties in the local economy.

Our identification strategy consists of analyzing the effect of Chapter 11 bankruptcies of large national retailers, such as Circuit City and Linens ‘n Things, who liquidate their entire store chain during the sample period. Using Chapter 11 bankruptcies of national retailers alleviates the concern that local economic conditions led to the demise of the company: it is unlikely that a large retail chain will suffer major financial difficulties because of a localized economic downturn in one of its many locations. Still, it is likely that national chains experiencing financial distress will restructure their operations and cherry-pick those stores they would like to remain open. According to this, financially distressed retailers will shut down their worst performing stores while keeping their best stores open, implying that a correlation between closures of stores of bankrupt chains may merely reflect poor local demand rather than negative externalities driven by financial distress. We address this concern directly by only utilizing variation driven by bankruptcy cases that result in the liquidation of the entire chain. In these cases, there is clearly no concern of cherry-picking of the more successful stores; all stores are closed regardless of local demand conditions.

In examining national chain liquidations, one concern that remains is that the stores of the liquidating chain were located in areas that experienced negative economic shocks—for example, because of poor store placement decisions made on the part of headquarters—and that it was these shocks that eventually drove the chain into bankruptcy. We address this concern in two ways. First, based on observables, we show empirically that stores of chains that eventually file for Chapter 11 bankruptcy and end up in full liquidations are not located in areas that are worse than the location of stores operated by chains that do not end up in bankruptcy. Second, due to our precise data on the location of each store and our use of area fixed effects (either county, zip code, or zip-by-year), our identification strategy enables us to net out local economic shocks and relies on variation within the relevant geographic area. As such, the relevant endogeneity concern is not that the stores of liquidating national chains were located in areas that suffered more negative economic shocks, but rather that these stores were somehow positioned in the worse locations *within each county or zip code*. Given their firms' success in forming a national chain of stores, this seems highly unlikely.

To further alleviate concerns about store locations we also perform a placebo test. We define a "placebo" variable that counts for each store in our sample the number of neighboring stores that are part of a national chain that will liquidate in the *following* year but that are currently not in bankruptcy. We find that the effect of store liquidation on subsequent store closures is not driven by the location of the retail chain-stores that will later become bankrupt but rather by the timing in which they were actually closed which is consistent with the existence of a causal effect of store closures.

2.3 Data and summary statistics

2.3.1 Sample construction and data sources

Our dataset is composed of several sources which we describe in turn in this section. The main source is Chain Store Guide (CSG), a database that contains detailed information on retail store locations in the US and Canada. CSG data is organized in the form of annual snapshots of almost the entire retail industry at the establishment level.[5] The information on each location contains the store name, its address (street number, street name, city, state, and zip code) and phone number, the parent company,

[5] CSG does not track locations operated by companies that have annual revenues below a certain industry-specific threshold. For example, to be included into the database, apparel retailers and department stores are required to have annual sales of at least $500,000 and $250,000, respectively.

and a CSG-defined industry.[6] Our sample covers the 2005-2010 period and includes 828,792 store-year observations in the U.S. in the following CSG-defined industries: Apparel Stores, Department Store, Discount Stores, General Merchandise Store, Home Centers & Hardware Chains, and Value-Priced Apparel Store. Figures 2.1 and 2.2 demonstrate the coverage of our data by plotting the locations of all stores in our dataset for the first year (2005 in Figure 2.1) and the last year of our sample (2010 in Figure 2.2).

We clean the data and streamline store names and parent names for consistency. Large chain stores account for the bulk of the data. For example, in 2010, the 50 largest retail chains accounted for 111,655 of the 166,045 stores in the dataset, representing 67.2% of the stores in the data for that year.

Our empirical strategy requires us to compute distances between retail locations. To do so we convert all street addresses into geographic coordinates using ArcGIS software. If an address is not contained in the address locator used by ArcGIS, we pass it through Google Maps API in an additional attempt to geocode it. As a result, we successfully map street addresses to geographic coordinates for 97% of the data. The information on longitudes and latitudes of full addresses—up to a street number—makes it possible for us to compute distances between retail locations to a very high precision. Since our analysis focuses on stores that are in close proximity to each other, we use the standard formula for the shortest distance between two points on a sphere (see Coval and Moskowitz (1999)) without adjusting for the fact that the Earth's surface is geoid-shaped.

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[6] The parent company is essentially the name of the retail chain. Some companies operate stores under different brands which we then match to the parent company.

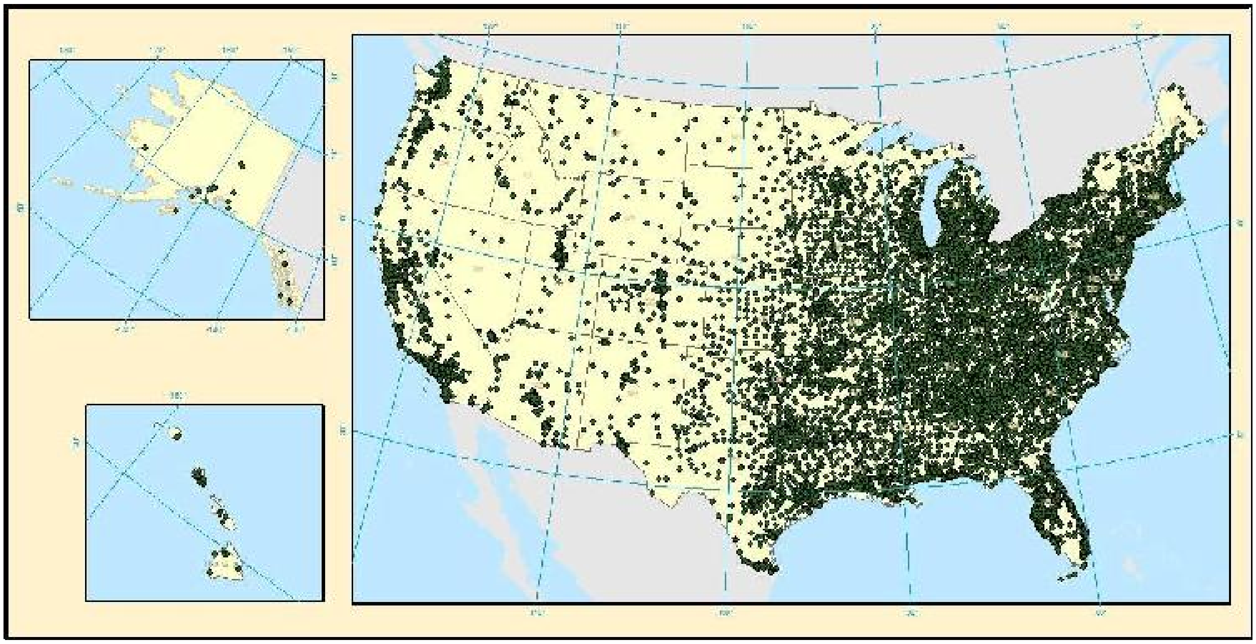

Figure 2.1: Store locations as of 2005

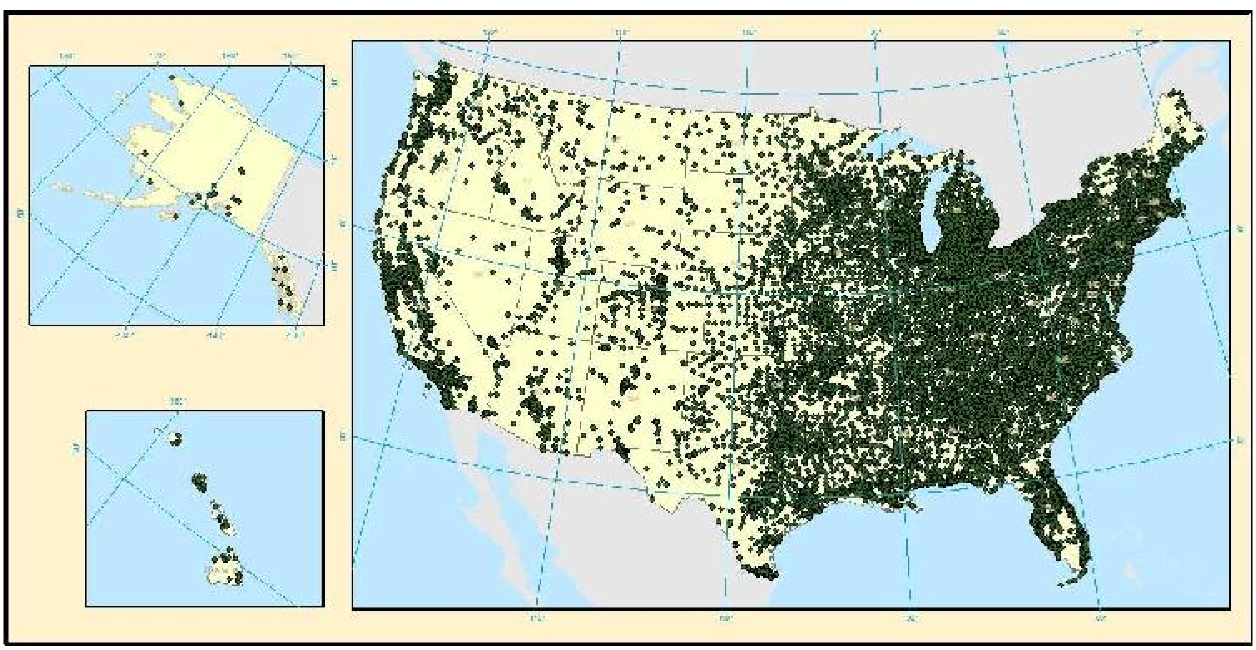

Figure 2.2: Store locations as of 2010

We supplement the CSG store-level data with information on the number of employees accessible through Esri's Business Analyst. Esri's data structure is very similar to that of CSG. We carefully merge these two databases by store/parent name and address; questionable cases are checked manually. The majority of information on the number of employees available is collected by Esri by reaching out individually to every store on a yearly basis; about 10% of the data though is populated according to the data provider's proprietary models based on observable characteristics of a retail location. In our analysis, we use only the actual data points and discard modeled figures.

We also use Esri's Major Shopping Centers, which is a panel of major U.S. shopping centers, to group stores in our sample into malls where applicable. The included mall-level pieces of information are mall name and its address (usually up to a street intersection), gross leasable area (GLA), total number of stores, and names of anchor tenants (up to four). We merge Esri's Major Shopping Centers to CSG data using the following multi-step procedure. First, we find anchor stores in the data using the information on store/parent name and zip code. If several anchor stores pertaining to the same mall are identified, we confirm the match if the average distance from anchors to the implied center of the mall is less than 200 meters. By doing so, we increase our confidence that we do not erroneously label stores as anchor tenants in zip codes containing a large number of stores. Stores located within 25 meters of anchors are assigned to the same mall. Second, we geocode addresses of malls that were not found in the data using anchor tenants—e.g., information on their anchors is missing—to be able to compute distances between malls and stores. All stores within 100 meters of the mall are assigned to that mall. At all stages of the algorithm, we manually check questionable cases by looking up store addresses and verifying whether they are part of a shopping mall.

Next, we use SDC Platinum to identify retail Chapter 11 bankruptcies since January 2000 within the following SIC retail trade categories: general merchandise (SIC 4-digit codes 5311, 5331 and 5399), apparel (5600, 5621 and 5651), home furnishings (5700, 5712, 5731, 5734 and 5735) and miscellaneous (5900, 5912, 5940, 5944, 5945, 5960, 5961 and 5990). There were 93 cases of retail Chapter 11 liquidations between 2000 and 2011. The largest bankruptcies in recent years include Circuit City, Goody's, G+G Retail, KB Toys, Linens 'n Things, Mervyn's, and The Sharper Image. Bankruptcy stores are identified in our data by their respective parent name.

We then merge our data with Compustat Fundamental and Industry Data. We use the Compustat North America Fundamentals Annual database to construct variables that are based on operational and financial data. These include the number of employees in the firm, size (defined as the natural log of total assets), market-to-book ratio (defined as the market value of equity and book value of assets less the book value of equity, divided by the book value of assets), profitability (defined as earnings over total assets), and leverage (defined as total current liabilities plus long-term debt, divided by the book value of assets).

We supplement our database with information pertaining to the local economies from the Census, IRS, Zillow, and the BLS. We rely on the 2000 Census survey for a host of demographic variables available by zip code. We also use the Internal Revenue Service (IRS) data which provides the number of filed tax returns (a proxy for the number of households), the number of exemptions (a proxy for the population), adjusted gross income (which includes taxable income from all sources less adjustments such as

IRA deductions, self-employment taxes, health insurance, alimony paid, etc.), wage and salary income, dividend income and interest income at the zip code level. We use data on house prices from Zillow, an online real estate database that tracks valuations throughout the United States. We construct annual county-level and zip-code median house values as well as annual changes in housing prices.

2.3.2 Individual store closures

In order to construct our main dependent variable of store closings we compare the data from one year to the next. We define a store closure if a store entry appears in a given year but not in the subsequent one. Given that our data span the years 2005-2010 we can identify store closings for each year from 2005 up to 2009. Panel A of Table 2.1 provides summary statistics on store closings during our entire sample-period as well as, individually, for each of the years in the sample. The number of stores in the data ranges from 84,388 individual stores in 2005 to 155,114 stores in 2009. The rate of annual store closure ranges between 1.4% in 2007 to 11.0% in 2008. During the entire sample period of 2005-2009, 6.1% of store-years represent store closures, with a standard deviation of 23.9%. Figures 2.3 and 2.4 display the geographical distribution of store closures (red dots) relative to stores that stay open (blue dots) for the years 2007 and 2008, respectively.

There are 30 retail companies that filed for bankruptcy and were matched to our 2005–2010 data set. Table 2.2 provides a chronological list of the bankrupt companies, the date in which they filed for bankruptcy, whether they emerged from bankruptcy, and the number of stores operated by the firm. Table 2.2 clearly demonstrates the wave of retail bankruptcies during the economic contraction of 2007–2009 as consumer consumption and expenditure declined sharply. In forming the sample of liquidating national chains used in our identification we include only those chains where upon bankruptcy of the chains all stores were closed, and in which the retail chains operated in several states.

Table 2.1: Individual store closures

Year	Mean	Standard deviation	Min	Max	N
Panel A: Closed stores over time					
2005–2009	0.061	0.239	0	1	661,382
2005	0.048	0.213	0	1	84,388
2006	0.085	0.279	0	1	125,897
2007	0.014	0.116	0	1	147,551
2008	0.110	0.313	0	1	148,432
2009	0.047	0.211	0	1	155,114
Panel B: Bankrupt stores over time					
2005–2010	0.021	0.142	0	1	827,156
2005	0.010	0.100	0	1	84,388
2006	0.008	0.091	0	1	125,897
2007	0.029	0.167	0	1	147,551
2008	0.042	0.201	0	1	148,432
2009	0.026	0.158	0	1	155,114
2010	0.004	0.063	0	1	165,774
Panel C: Stores closed in full liquidation bankruptcies over time					
2005–2009	0.010	0.100	0	1	661,382
2005	0.002	0.049	0	1	84,388
2006	0.003	0.058	0	1	125,897
2007	0.001	0.033	0	1	147,551
2008	0.019	0.135	0	1	148,432
2009	0.019	0.137	0	1	155,114

Notes: This table provides descriptive statistics on store closings and bankrupt stores. Panel A displays all store closings. Panel B presents bankrupt stores, Panel C presents store closings that result from full liquidation bankruptcies.

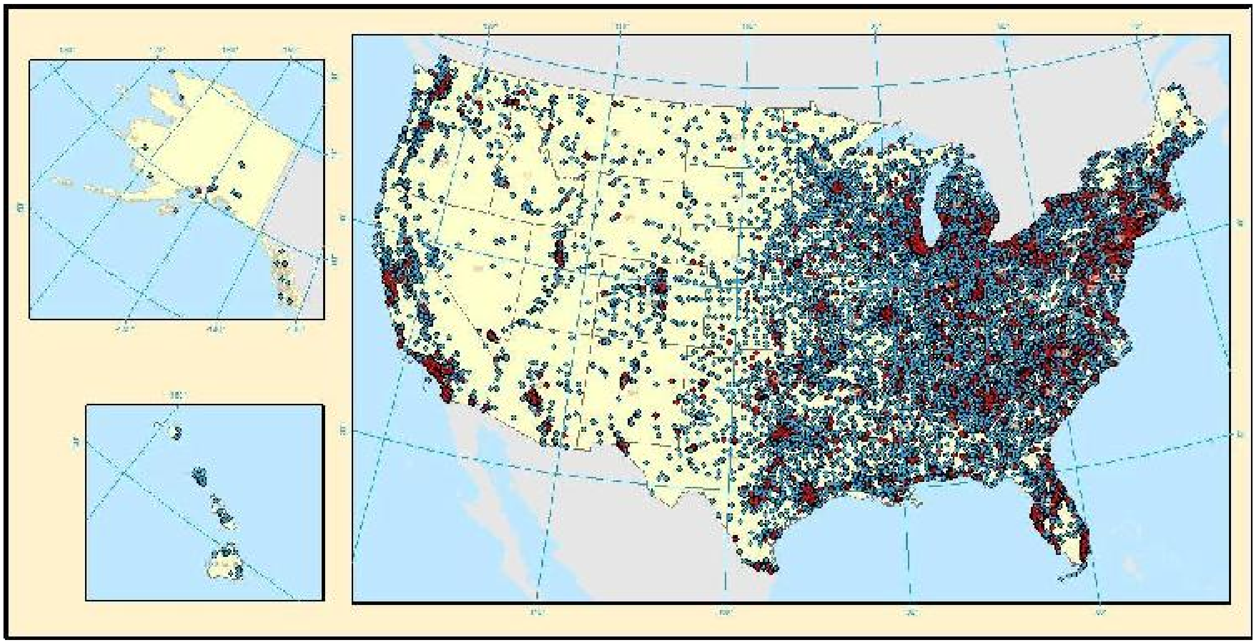

Figure 2.3: Store closures during 2007

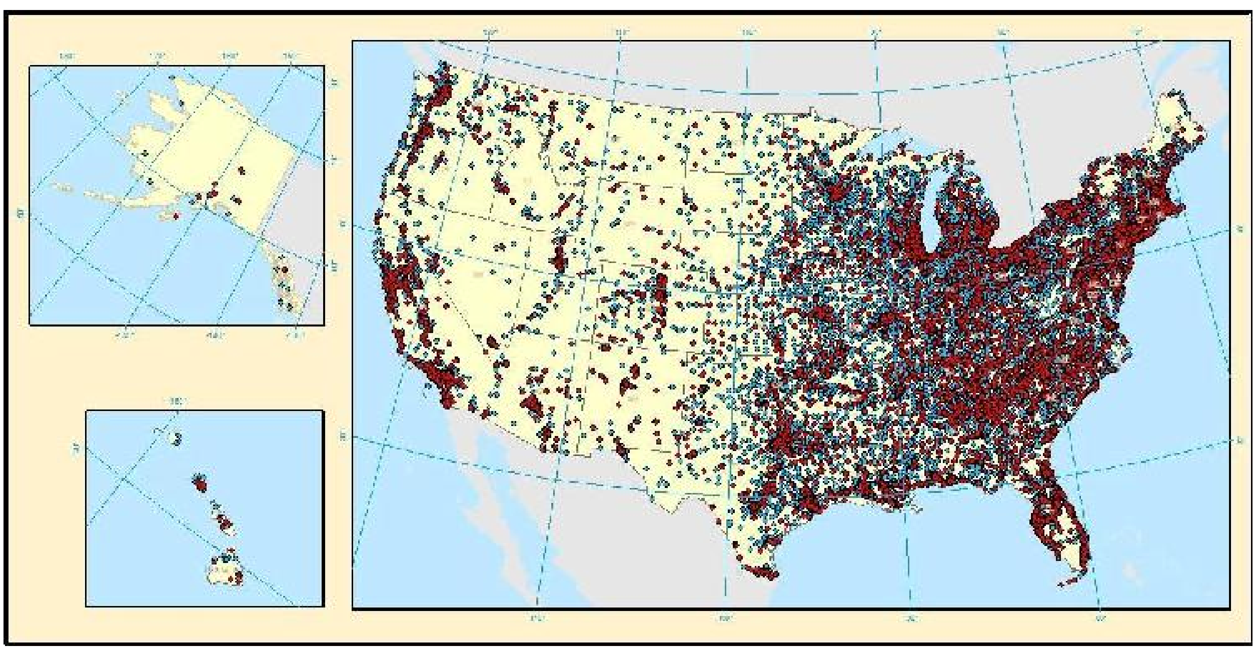

Figure 2.4: Store closures during 2008

Table 2.2: Bankrupt retail companies

Company	Filing date	Emerged	Used in identification	Bankruptcy outcome	Date disposed	# of stores
Gadzooks	02/03/04	No	No	Acq.	02/17/06	243
Ultimate Electronics	01/11/05	No	No	Acq.	12/09/05	65
D K Stores	04/08/05	No	Yes	Liq.	02/09/06	54
Norstan Apparel Shops	04/08/05	No	Yes	Acq.	05/26/05	229
G+G Retail	01/25/06	No	Yes	Liq.	12/06/06	515
Tower Record	08/20/06	No	Yes	Liq.	08/06/07	89
KS Merchandise Mart	10/03/06	No	Yes	Liq.	N/A	17
Hancock Fabrics	03/21/07	Yes	No	Reorg.	08/01/08	373
The Dunlap	07/10/07	No	Yes	Liq.	N/A	38
The Sharper Image Corporation	02/19/08	No	Yes	363 sale	08/13/12	184
Linens 'n Things	05/02/08	No	Yes	363 sale	06/12/09	589
Mervyn's	07/29/08	No	Yes	Liq.	10/27/08	177
Boscov's	08/04/08	No	No	Liq.	12/04/07	49
Value City Department Stores	10/26/08	No	Yes	Liq.	02/26/09	66
Tweeter Home Entertainment Group	11/05/08	No	Yes	363 sale	07/13/07	104
National Wholesale Liquidators	11/10/08	No	Yes	Liq.	N/A	55
Circuit City Stores	11/10/08	No	Yes	363 sale	09/20/10	721
KB Toys	12/11/08	No	Yes	Liq.	02/16/10	461
Goody's	01/13/09	No	Yes	Liq.	07/03/09	287
Gottschalks	01/14/09	No	Yes	Liq.	02/28/11	58
Rex Stores	02/01/09	No	Yes	Liq.	N/A	111
S & K Famous Brands	02/09/09	No	Yes	Liq.	03/16/10	136
Ritz Camera Centers	02/22/09	Yes	No	Reorg.	N/A	N/A
Joe's Sports Outdoors More	03/24/09	No	Yes	Liq.	04/14/09	31
Filene's Basement	05/24/09	No	No	Liq.	02/10/10	25
Eddie Bauer Holdings	06/17/09	No	No	363 sale	03/18/10	371
Movie Gallery	02/02/10	No	Yes	Liq.	11/18/10	2,415
Loehmann's Holdings	11/15/10	Yes	No	Reorg.	02/09/11	48

Notes: This table provides information on the main retail bankruptcy cases used in our analysis. The table lists the name of the bankrupt company, its bankruptcy filing date, whether it emerged or not from bankruptcy, the bankruptcy outcome, the date in which the case was disposed, the time spent in bankruptcy and the number of stores operated by the company in the time of the bankruptcy filing. Acq. = acquired; Liq. = liquidated; reorg. = reorganized.

Panel B of Table 2.1 provides summary statistics for stores that operated while their company was in a Chapter 11 restructuring. As Panel B shows, 2.1% of the 827,156 observations were stores that their companies were operating under Chapter 11 protection. The number of bankrupt stores increased sharply from 4,231 stores in 2007 (representing 2.9% of total stores) to 6,167 bankrupt stores in 2008 (4.2% of total stores). By 2009 many of the bankrupt retailers were liquidated and their stores disappeared resulting in fewer bankrupt stores (3,963 stores representing 2.6% of the stores in our sample). By 2010 most of the remaining bankrupt companies that were not liquidated emerged from Chapter 11 and the number of bankrupt stores fell to 652 or 0.4% of the stores in our sample.

Finally, we calculate the number of stores that were closed in bankruptcies of chains that were fully liquidated. As we argue previously, these bankruptcy cases are not driven by the specific location of their stores but rather because of a failure of their business plan. Hence, as described in the Identification Strategy section, we use store closures resulting from the chain-wide liquidation of the parent firm to capture the negative externalities of bankruptcy. Panel C of Table 2.1 displays summary statistics for these chain-wide liquidating stores. The number of stores closed by chains that were fully liquidated in bankruptcy increases from 160 stores in 2007 (0.10% of total stores) to 2,650 (1.86% of total stores) and 2,987 (1.93% of total stores), in 2008 and 2009, respectively.[7]

[7] As in Panel A of Table 2.1 we cannot calculate stores closing for 2010 given that it is the last year in our panel dataset.

2.3.4 Neighboring store closures

We construct three main measures of neighboring store closures that are driven by liquidation of national retail chains. To do this, for each store in our sample and for every year we measure the distance to any other store in our sample. Specifically, for each store we define its neighboring stores in a series of concentric circles. We consider neighboring stores that are: (1) located in the same address; (2) located in a different address but are within a 50 meters radius of the store under consideration; and (3) stores that are located in a different address and are located in a radius of more than 50 meters but less or equal than 100 meters from the store under consideration.[8] In each of these three geographical units, for each store and each year, we then count the number of stores that were closed as a result of a full liquidation of a large retail chain.

Table 2.3 provides summary statistics for the three measures associated with each of the three geographical units, as well as for counts of neighboring stores that are outside of the 100 meters radius. Panel A of Table 2.3 displays summary statistics for same address stores that were closed in chain liquidations. During the 2005-2010 same-address liquidated stores ranged from 0 to 3 with an unconditional mean of 0.028 and a standard deviation of 0.181. For any given store, therefore, the maximum number of stores operating in the same address that were closed as a result of a retail-chain liquidation is three. Panel A also displays the evolution of the *same-address* measure over time. For example, on average *same-address* equals 0 and 0.002 in 2005 and 2006, respectively.[9] As the number of bankruptcies rose in 2007 *same-address* increased to

[8] Different stores that are operating in the same address are usually indicative of a shopping mall.

[9] The first statistic here simply reflects the fact that there were no store closures as a result of retail-chain liquidations in 2005.

Table 2.3: Neighboring store closures

Year	Mean	Standard deviation	Min	Max	N
Panel A: Same address					
2005–2010	0.028	0.181	0	3	827,156
2005	0.000	0.000	0	0	84,388
2006	0.002	0.045	0	1	125,897
2007	0.038	0.192	0	2	147,551
2008	0.016	0.127	0	2	148,432
2009	0.085	0.327	0	3	155,114
2010	0.009	0.100	0	2	165,774
Panel B: Not same address and distance ≤ 50 meters					
2005–2010	0.012	0.115	0	3	827,156
2005	0.000	0.000	0	0	84,388
2006	0.002	0.044	0	1	125,897
2007	0.009	0.099	0	2	147,551
2008	0.003	0.055	0	2	148,432
2009	0.038	0.207	0	3	155,114
2010	0.010	0.111	0	2	165,774
Panel C: 50 meters < distance ≤ 100 meters					
2005–2010	0.008	0.094	0	3	827,156
2005	0.000	0.000	0	0	84,388
2006	0.001	0.030	0	1	125,897
2007	0.005	0.075	0	2	147,551
2008	0.002	0.044	0	1	148,432
2009	0.025	0.166	0	3	155,114
2010	0.008	0.103	0	2	165,774
Panel D: Further away store closures 2005–2010					
100–150 meters	0.007	0.087	0	3	827,156
150–200 meters	0.006	0.085	0	3	827,156
200–250 meters	0.020	0.151	0	4	827,156
250–300 meters	0.006	0.082	0	3	827,156
300–350 meters	0.006	0.083	0	4	827,156
350–400 meters	0.006	0.079	0	3	827,156
400–450 meters	0.006	0.081	0	3	827,156
450–500 meters	0.006	0.079	0	4	827,156

Notes: This table provides descriptive statistics on full liquidation closings of neighboring stores. Panel A displays store closings in the same address. Panels B and C present store closings for 0-50 meter and 50-100 meter distances. Panel D lists summary statistics for distances that are between 150 and 500 meter.

0.038 in 2007 (range between 0 and 2) and peaked at 0.085 (range between 0 and 3) in 2009.

Panels B and C present similar statistics for the $0 < distance \leq 50$ and the $50 < distance \leq 100$ measures, respectively. As can be seen, both measures display similar patterns over time ranging from 0 to 3 and averaging approximately 0.01. Finally, Panel D expands the concentric rings beyond 100 meters, and displays summary statistics for distances up to 500 meters, at 50 meter interval.

2.4 Stores locations

2.4.1 The geographical dispersion of liquidated chain stores

One of the main pillars of our identification strategy is the conjecture that large bankruptcy cases of national retail chains are less likely to be driven by localized economic conditions given their diversity and geographical dispersion. We present the case for the geographical dispersion of these chains in Table 2.4 by listing information on the geography of operation of the retail chain bankruptcies utilized in our empirical strategy.[10] In choosing these cases we focus on those bankruptcy cases of retail chains that operated in several states and that end up in full liquidation of all the stores.

Table 2.4: Retail chains fully liquidated

Company	# of stores	# of states	# of census divisions	Largest census division
Circuit City Stores	570	44	9	S. Atlantic
D K Stores	54	5	3	Mid Atlantic
Discovery Channel Retail Stores	107	32	9	Pacific
G+G Retail	314	40	9	S. Atlantic

[10] Note that the Discovery Channel Retail Stores liquidation did not result from a Chapter 11 filing but rather from a voluntary closure of the entire chain.

Table 2.4: Retail chains fully liquidated (Continued)

Company	# of stores	# of states	# of census divisions	Largest census division
Goody's	377	21	5	S. Atlantic
Gottschalks	60	6	2	Pacific
Joe's Sports Outdoors More	26	2	1	Pacific
KB Toys	483	44	9	Mid Atlantic
KS Merchandise Mart	18	5	3	E. N. Central
Linens 'n Things	496	48	9	S. Atlantic
Mervyn's	169	8	3	Pacific
Movie Gallery	2,831	50	9	Pacific
National Wholesale Liquidators	44	12	4	Mid Atlantic
Norstan Apparel Shops	147	21	6	S. Atlantic
Rex Stores	113	34	9	S. Atlantic
S & K Famous Brands	43	11	5	S. Atlantic
The Dunlap	38	8	4	W. S. Central
The Sharper Image Corporation	178	38	9	Pacific
Tower Record	88	20	8	Pacific
Tweeter Home Entertainment Group	104	22	8	S. Atlantic
Value City Department Stores	105	15	5	E. N. Central

Notes: This table provides information on the geographical dispersion of the liquidated retail chains used in the analysis.

There are 21 such cases in the data affecting a total of 6,418 individual stores in our sample. The mean (median) number of stores of these retail chains is 305.6 (113) and ranges from 18 stores (KS Merchandise Mart) to 2,831 (Movie Gallery). All retail chains operate in more than one state, with the least diversified chain operating in only two states (Joe's Sports Outdoors More) and the most geographically dispersed chain operating in all fifty states (Movie Gallery). Finally, as the last two columns of Table 2.4 demonstrate, all chain except Joe's Sports Outdoors More operate in more than one region of the U.S. For example, eight chains have operations in all nine census divisions, and 19 out of the 21 retail chain operate stores in at least four different census divisions. While two retailers seem to be less geographically dispersed (Joe's Sports Outdoors More and Gottschalks) they do not drive our results and excluding them from the calculation of liquidated stores does not affect our findings. Furthermore, Figures 2.5, 2.6, and 2.7 illustrate the geographical dispersion of the initial stores locations of three firms that ended up in full liquidation used in the empirical identification: Circuit City, Linens 'N Things, and The Sharper Image. As the figures demonstrate, and consistent with the statistics in Table 2.4, these retail companies had dispersed geographical operation.

Given their geographic dispersion, it is unlikely that the collapse of these chains is driven by localized economic shocks related to a particular store or sub-area. Of course, this does not rule out the concern that nation-wide, liquidating stores were positioned in worse locations. We address this concern in the next section.

2.4.2 The initial location of liquidated chain stores

The previous section presents evidence that most liquidated chains are geographically dispersed across states and U.S. regions. In this section we show that stores of liquidated chains were not located in zip codes with worse economic characteristics than the location of stores operated by non-bankrupt chains. We start by comparing the means of several local economic indicators between chains that end-up in full liquidations and chains with similar business that do not end-up in bankruptcy during the sample period. The local economic indicators that we use are the natural log of adjusted gross income income at the zip code in 2006; the natural log of median house value at the zip code in the 2000 Census; and the percentage change in median house price during the period 2002-2006 in the zip code which is based on data from Zillow. We focus on the year 2006 since economic slowdown began already in 2007.

It is important to note that we compare the locations of chains to otherwise similar chains two years *before* the liquidated chains file for bankruptcy. We present summary statistics for the three chains presented in Figures 2.5, 2.6, and 2.7: Circuit City, Linen `n Things, and The Sharper Image. Each of the chains is matched to a similar chain that does not end-up in bankruptcy and liquidation during the sample period. We compare Circuit City and Best Buy; Linen `n Things and Bed Bath & Beyond; and The Sharper Image to Brookstone. As Table 2.5 illustrates, there are no statistically significant differences in the three local economic indicators that pertain to store locations between the chains that will end-up in liquidations and their comparable chains.

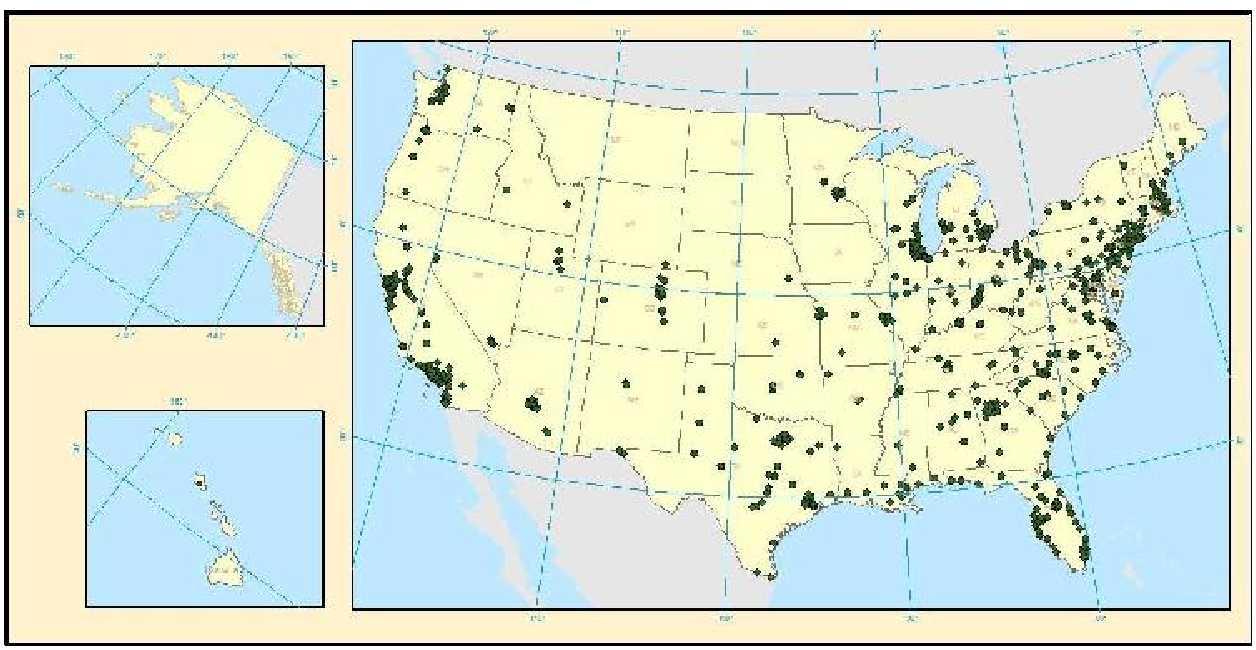

Figure 2.5: Store locations of Circuit City

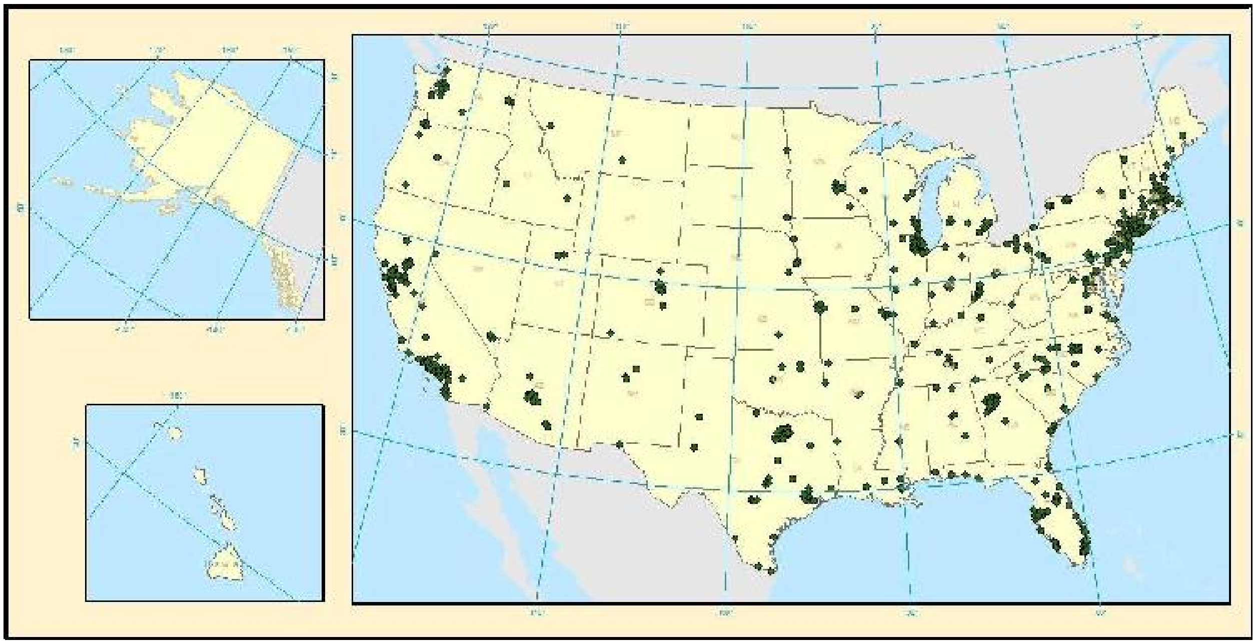

Figure 2.6: Store locations of Linens 'n Things

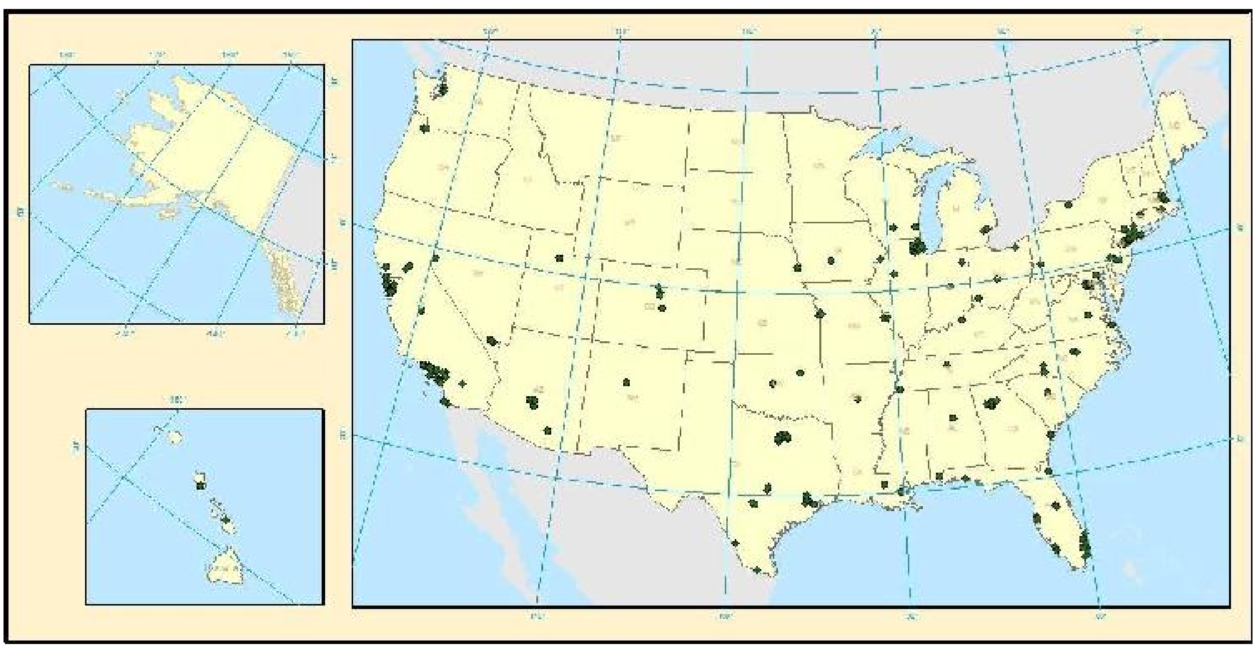

Figure 2.7: Store locations of The Sharper Image

Table 2.5: Comparison of store locations

Company	log(adjusted gross income)	log(median house value)	Δ(house value 2002–2006)	# of stores
Circuit City Stores	4.08	11.81	0.63	607
Best Buy	4.09	11.82	0.60	729
p-value	0.799	0.625	0.164	
Linens 'n Things	4.12	11.91	0.61	511
Bed Bath & Beyond	4.11	11.87	0.60	700
p-value	0.308	0.119	0.598	
The Sharper Image	4.17	12.19	0.68	181
Brookstone	4.16	12.02	0.69	269
p-value	0.983	0.000	0.635	

Notes: This table compares the means of log(adjusted gross income), log(median house value), and Δ(house value 2002–2006) across all the stores of fully liquidated chains and similar chains that were not liquidated for a three selected chains. Means are calculated based on store locations in 2006. P-values are calculated using a two-sample t-test assuming equal variances for the hypothesis that the difference in the means is different from zero.

While Table 2.5 presents univariate analysis for three chains we now move to estimate the relation between local economic conditions and store location for all the liquidated chains in our data. We run a linear probability model of future store liquidation -- testing the relation between belonging to a chain that eventually ends up in liquidation and local economic indicators. We estimate the following regression:

$$Liquidated_{i,z,t} = \alpha + \beta_1 \log(median\ income)_{z,t} + \beta_2 \log(house\ value)_{z,2000} \tag{1}$$
$$+ \beta_3 \%\Delta house\ price_{2002-2006,z} + \beta_4 Mall_i + \mathrm{b}_i\delta + \epsilon_{i,t}$$

where the dependent variable is an indicator variable that is set equal to one if a store is operated by a national retail chain that will end up in liquidation at some point in the future, and zero otherwise; $\log(median\ income)_{z,t}$ is the natural log of median adjusted gross income at the zip code in either 2005 or 2006; $\log(house\ value)_{z,2000}$ is the natural log of median house value at the zip code in the 2000 Census; $\%\Delta\ house\ price_{2002-2006,z}$

is the percentage change in median house price during the period 2002-2006 in the zip code and is based on data from Zillow; Mall is a dummy variable that takes the value of one if the store is located in a large shopping mall, and zero otherwise; and b is a vector of county fixed effects. The coefficients of interest are β_1, β_2, and β_3 which measure the effect of local economic conditions on store location. Table 2.6 presents the results from estimating different variants of the model and displays standard errors (in parentheses) that are clustered at the zip code level as we do throughout the paper. Given that the location of a specific store does not change over time we estimate separate cross-sectional rather than panel regressions for the years 2005 and 2006.

Table 2.6: Determinants of store locations

(Sub)sample:	All stores	Non-mall stores	Mall stores	All stores	Non-mall stores	Mall stores
	(1)	(2)	(3)	(4)	(5)	(6)
log(median household income)	0.007	0.010	-0.017	-0.007	0.001	-0.035
	[0.009]	[0.010]	[0.035]	[0.007]	[0.001]	[0.030]
log(median house value)	0.002	0.004	-0.010	0.008***	0.010***	-0.007
	[0.003]	[0.003]	[0.011]	[0.002]	[0.002]	[0.008]
Median house price growth,	0.000	0.000	-0.003	-0.001	-0.001	-0.003
2002–2006	[0.004]	[0.004]	[0.016]	[0.003]	[0.003]	[0.009]
Mall	0.037***			0.028***		
	[0.003]			[0.002]		
Year	2005	2005	2005	2006	2006	2006
Fixed effects	County	County	County	County	County	County
Observations	52,597	44,488	8,109	76,057	62,808	13,249
Adjusted-R-squared	0.013	0.010	0.043	0.002	0.007	0.030

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of stores locations. The tables uses zip-code level economic controls and all regressions include an intercept, and county fixed effects (not reported). Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

As the first column of Table 2.6 demonstrates, stores of national retail chains that end-up in liquidation after the year 2005 are located in zip codes with economic characteristics that are not statistically different from zip codes of stores belonging to chains that do not end up in liquidation. The only difference between stores of chains that end in liquidations and other stores is that the former are more likely to be located in shopping malls. In Columns 2 and 3 of Table 2.6 we split the sample between non-mall stores (Column 2) and stores located in a mall (Column 3). As Table 2.6 illustrates, store locations of chains that end up in full liquidation are again not different from the location of other stores when we stratify the data by a mall indicator.

Columns 4, 5 and 6 repeat the store location analysis in Columns 1, 2 and 3 but for the year 2006 rather than 2005. Again, the results show that stores of retail chains that end up in liquidation are located in zip codes that are similar to the location of other stores in terms of median household income and house price appreciation. As the table demonstrates, the difference between the location of liquidated chain stores and the location of non-liquidated chain stores is that stores of liquidated chains are located in zip-codes with slightly higher median house values in 2000.

In summary, Table 2.6 demonstrates that along the observables there are no significant differences between the location of liquidated chain stores and the location of stores belonging to retail chains that do not undergo liquidation in 2005. Moreover, the only slight difference in terms of location is that liquidated chain stores are more likely to be located in zip codes with slightly higher median house values in 2006. These results confirm that the initial location of stores of national chains that end up in liquidation is not a likely cause of their failure. Thus, given the geographical dispersion of these chains and the zip codes in which they are located, closures of these stores are unlikely to be driven by worse local economic conditions. However, one remaining concern is that the locations of liquidating national chains suffered more during the economic downturn even though their initial location was no worse. As discussed below we address this point directly through the inclusion zip-by-year fixed effects.

2.5 The effect of bankruptcy on store closures

2.5.1 Baseline regressions

We begin with a simple test of the negative externalities hypothesis by estimating a linear probability model of store closures conditional on the liquidation of neighboring stores that result from a national retailer chain-wide liquidation. We estimate different variants of the following baseline specification.

$$\begin{aligned} Closed_{i,t} = \alpha &+ \beta_1 n(same\ address)_{i,t-1} + \beta_2 n(0 < distance \leq 50)_{i,t-1} \\ &+ \beta_3 n(50 < distance \leq 100)_{i,t-1} + \beta_4 \log(income\ per\ household)_{z,t} \\ &+ \beta_5 income\ growth_{z,t} + \mathrm{b}_i\delta + \mathrm{d}_t\theta + \epsilon_{i,t} \end{aligned} \tag{2}$$

where the dependent variable is an indicator variable equal to one if a store is closed in a given year, and zero otherwise; n(same address), n($0 < distance \leq 50$), and n($50 < distance \leq 100$) are the number of stores that were closed in bankruptcies of chains that were fully liquidated and that are (1) located in the same address; (2) located in a different address but are within a 50 meters radius of the store under consideration; and (3) stores that are located in a radius of more than 50 meters but less than 100 meters from the store under consideration, respectively. log(income per household) is a zip-code level median adjusted gross income per capita; income growth is the annual growth rate in adjusted gross income per household within a zip code, both income measures are constructed from the IRS data. b is a vector of either state, county or zip code fixed effects; $\mathbf{d}$ is a vector of year fixed effects and ϵ is a regression residual. We focus our analysis on stores of chains that are not currently undergoing a national liquidation to avoid mechanical correlation between the dependent and explanatory variables.[11] That is, we eliminate from the sample stores that are operated by the retail chains reported in Table 2.4 during their bankruptcy years. Table 2.7 presents the results from estimating different variants of the model and displays standard errors (in parentheses) that are clustered at the zip code level.

Table 2.7: Neighboring bankrupt stores and store closures

	(1)	(2)	(3)	(4)	(5)	(6)
Full liquidation bankrupt store closures$_{t-1}$						
same address	0.0036**	0.0037**	0.0042***	0.0065***	0.0030**	0.005***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
distance $\leq$ 50 meters	0.0003	0.0005	0.0002	-0.0024	-0.0010	-0.0020
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
50 $<$ distance $\leq$ 100 meters	0.0019	0.0024	0.0022	0.0007	0.0020	0.0030
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Ln(income per household)	0.0066***	0.0052***	-0.0049	-0.0650***		
	[0.002]	[0.002]	[0.003]	[0.009]		
Income growth	-0.0328***	-0.0381***	-0.0304***	0.0071		
	[0.009]	[0.009]	[0.009]	[0.011]		
Fixed effects	Year	Year & State	Year & County	Year & Zip	Year-by-County	Year-by-Zip
Observations	654,581	654,581	654,581	654,581	654,581	654,581
Adjusted R-squared	0.021	0.021	0.027	0.062	0.050	0.160

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures. All regressions include an intercept and year fixed effects. Models 2, 3, and 4 include state, county, and zip-code fixed effects, respectively. Model 5 includes county*year and Model 6 includes zip*year fixed effects. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[11] See Angrist and Pischke (2009) page 196.

Column 1 of Table 2.7 presents the results of regression (2) using only year fixed effects. As can be seen, there is a positive relation between the number of stores closed as part of a national chain-wide liquidation and the probability that stores of non-bankrupt firms in the same address will close. Thus, consistent with the externalities conjecture, increases in bankruptcies and store closures are associated with further closings of neighboring stores. The effect is economically sizable: being located in the same address as a liquidating retail-chain store increases the probability of closure by 0.36 percentage points, or 5.9 percent of the sample mean. We also find that the negative effect of store closures is confined to stores located in the same address given that the coefficients on both n($0 < distance \leq 50$) and n($50 < distance \leq 100$) are not statistically different from zero. As shown below, once heterogeneity is added to the analysis we capture effects at longer distances.

Column 2 of the table repeats the analysis in Column 1 while adding state fixed effects to the specification. As can be seen, the results remain qualitatively and quantitatively unchanged: bankruptcy induced stores closures lead to additional closings of stores in the same area. Columns 3 and 4 repeat the analysis but add either county or zip-code fixed effects to the specification and hence control for unobserved heterogeneity at a finer geographical level. As can be seen in the table, we continue to find a positive relation between stores that are closed in full liquidation bankruptcies and subsequent store closures in the same address.

Further, the inclusion of either county or zip-code fixed effects increases the marginal effect of same address store closures considerably from 0.0036 and 0.0037 to 0.0042 and 0.0065 in the county and zip fixed effects specifications, respectively. Thus, Table 2.7 demonstrates that having one neighboring store close down as part of a national retail liquidation increases the likelihood that stores in the same address will close by between 5.9 and 10.7 percent relative to the unconditional mean.[12] The results point to agglomeration economies in retail, as the reduction of store density in a given locality exhibits a negative effect on other stores in the area, increasing their likelihood of closure. This is consistent with evidence in Gould and Pashigian (1998) and Gould, Pashigian, and Prendergast (2005) which show that store level sales may depend on the sales of neighboring stores.

Finally, Columns 5 and 6 include county-by-year or zip-code-by-year fixed effects and hence control for unobserved *time-varying* heterogeneity at a fine geographical level. The inclusion of these fixed effects soaks-up any time-varying local economic conditions that may be correlated with the likelihood of store closures. As can be seen in Columns 5 and 6 we continue to find a positive relation between stores that are closed in full liquidation bankruptcies and subsequent store closures in the same address. These results alleviate concerns that the locations of liquidating national chains suffered more during the economic downturn even though their initial location was no worse.

Turning to the control variables in Table 2.7, in the first three columns the coefficient of log(income per household) is either positive or not statistically significant in explaining individual store closures. Moreover, as would be expected, the first three columns of Table 2.7 also suggest that stores are less likely to be closed in zip codes in which income grows over time. Furthermore, in our specifications that include zip-code fixed effects in which we control for unobserved geographical heterogeneity at a finer

[12] The fact that the relevant coefficients rise after including county or zip level fixed effects may be suggestive of the fact that stores of liquidating retail chains are located, if anything, in better areas on average, as seen above.

level (Column 4) we find that income per household has a negative and significant effect on the likelihood that a store closes down, again, as one would expect.

2.5.1.1 Neighboring bankrupt stores and closing of stores by distance

We next turn to estimate the externalities effects of further away store closures. We supplement the analysis in Table 2.7 by adding additional distance ranges to the specification in regression (2). Specifically, we estimate the following model:

$$\begin{aligned} Closed_{i,t} = \alpha &+ \beta_1 n(same\ address)_{i,t-1} + \beta_2 n(0 < distance \leq 50)_{i,t-1} \\ &+ \beta_3 n(50 < distance \leq 100)_{i,t-1} + \beta_4 n(100 < distance \leq 150)_{i,t-1} \\ &+ \beta_5 n(150 < distance \leq 200)_{i,t-1} + \beta_6 n(200 < distance \leq 250)_{i,t-1} \\ &+ \beta_7 n(250 < distance \leq 300)_{i,t-1} + \beta_8 n(300 < distance \leq 350)_{i,t-1} \\ &+ \beta_9 n(350 < distance \leq 400)_{i,t-1} + \beta_{10} n(400 < distance \leq 450)_{i,t-1} \\ &+ \beta_{11} n(500 < distance \leq 500)_{i,t-1} + \beta_{12} \log(income\ per\ household)_{z,t} \\ &+ \beta_{13} income\ growth_{z,t} + \mathrm{b}_i\delta + \mathrm{d}_t\theta + \epsilon_{i,t} \end{aligned} \tag{3}$$

Table 2.8 reports the results of regression (3) using the four different fixed effects specifications used in Table 2.7. As the table demonstrates, out of the eleven distance measures, β_1—the coefficient on n(same address)—is the only estimate that is both statistically and economically significant. While β_1 ranges from 0.004 (in the year fixed effects specification) to 0.007 (in the zip-code fixed effects specification), almost all the other estimates are much smaller and are not statistically different from zero. Only the coefficient on n($300 < distance \leq 350$) is negative and marginally significant. The results in Table 2.8 confirm our baseline results and demonstrate that when analyzing average effects the negative externality of store closures is mostly driven by very near stores. However, we return to this result below when analyzing the externality effect of store closures on neighboring stores belonging to chains of differing financial health and differing industries.

Table 2.8: Neighboring bankrupt stores and store closures by distance

	(1)	(2)	(3)	(4)
Full liquidation bankrupt store closures$_{t-1}$				
same address	0.004**	0.004**	0.004***	0.007***
	[0.002]	[0.002]	[0.002]	[0.002]
distance $\leq$ 50 meters	0.000	0.000	0.000	-0.002
	[0.002]	[0.002]	[0.002]	[0.002]
50 < distance $\leq$ 100 meters	0.002	0.002	0.002	0.001
	[0.003]	[0.003]	[0.003]	[0.003]
100 < distance $\leq$ 150 meters	0.002	0.002	0.002	0.002
	[0.004]	[0.004]	[0.004]	[0.005]
150 < distance $\leq$ 200 meters	0.003	0.003	0.002	0.001
	[0.005]	[0.005]	[0.005]	[0.005]
200 < distance $\leq$ 250 meters	-0.001	0.000	0.000	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]
250 < distance $\leq$ 300 meters	0.003	0.004	0.003	0.001
	[0.004]	[0.004]	[0.004]	[0.004]
300 < distance $\leq$ 350 meters	-0.003	-0.002	-0.003	-0.005*
	[0.003]	[0.003]	[0.003]	[0.003]
350 < distance $\leq$ 400 meters	0.002	0.003	0.003	0.000
	[0.003]	[0.003]	[0.003]	[0.003]
400 < distance $\leq$ 450 meters	0.004	0.005	0.004	0.001
	[0.004]	[0.004]	[0.003]	[0.003]
450 < distance $\leq$ 500 meters	0.005	0.005	0.002	-0.001
	[0.007]	[0.007]	[0.006]	[0.006]
Ln(income per household)	0.007***	0.005***	-0.005	-0.065***
	[0.002]	[0.002]	[0.003]	[0.009]
Income growth	-0.033***	-0.038***	-0.030***	0.007
	[0.009]	[0.009]	[0.009]	[0.011]
Fixed effects	Year	Year & State	Year & County	Year & Zip
Observations	654,581	654,581	654,581	654,581
Adjusted R-squared	0.021	0.022	0.027	0.062

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures. All regressions include an intercept and year fixed effects. Models 2, 3, and 4 include state, county, and zip-code fixed effects, respectively. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

2.5.2 Falsification exercise: placebo regressions

We supplement our analysis by performing a placebo exercise, the results of which are reported in Table 2.9. For each of the distance measures in Regression (2) and Table 2.7 we define a "placebo" variable which counts for each store in our sample the number of neighboring stores that are part of a national chain that will liquidate in the *following* year but that are currently not in liquidation. Following our baseline regression, we define these placebo variables for each of the three distance groups—same address, up to 50 meters and above 50 meters but below 100 meters. Thus, the falsification variables are simply the distance based liquidating store closure counter variables forwarded one period ahead. We then run the following variant of our baseline specification:

$$\begin{aligned} Closed_{i,t} = \alpha &+ \beta_1 n(same\ address)_{i,t-1} + \beta_2 n(0 < distance \leq 50)_{i,t-1} \\ &+ \beta_3 n(50 < distance \leq 100)_{i,t-1} + \beta_4 n(same\ address)_{i,t+1} \\ &+ \beta_5 n(0 < distance \leq 50)_{i,t+1} + \beta_6 n(50 < distance \leq 100)_{i,t+1} \\ &+ \beta_7 \log(income\ per\ household)_{z,t} + \beta_8 income\ growth_{z,t} \\ &+ \mathrm{b}_i \delta + \mathrm{d}_t \theta + \epsilon_{i,t} \end{aligned} \tag{4}$$

where the first three variables are the lagged store closure counter variables and the following three variables are the forwarded store closure counter variables. By including both lagged and forwarded variables, we attempt to uncover the time-stamp of the store-closure externality separately from the endogenous (soon to be bankrupt) retail-chain store location. Since the externality of store closure is likely to arise only *after* the store closes—as only then does costumer traffic drop—the externality effect predicts that the forwarded variables will not be significant while the lagged variables will be significant. In contrast, if the locations of liquidating chain stores were endogenous and correlated with omitted variables that predict local store closure, we would expect to find the forwarded variables positively related to store closure.

Table 2.9: Neighboring bankrupt stores and placebo store closures

	(1)	(2)	(3)
Full liquidation bankrupt store closures$_{t-1}$			
same address	0.004***	0.005***	0.007***
	[0.002]	[0.002]	[0.002]
distance ≤ 50 meters	0.001	0.000	-0.002
	[0.002]	[0.002]	[0.002]
50 < distance ≤ 100 meters	0.002	0.002	0.001
	[0.003]	[0.003]	[0.003]
Placebo full liquidation bankrupt store closures$_{t+1}$			
same address	-0.0060***	-0.0054***	-0.002
	[0.001]	[0.001]	[0.001]
distance ≤ 50 meters	-0.002	-0.002	-0.001
	[0.002]	[0.002]	[0.002]
50 < distance ≤ 100 meters	0.001	0.002	0.002
	[0.003]	[0.003]	[0.003]
Ln(income per household)	0.0053***	-0.005	-0.0647***
	[0.002]	[0.003]	[0.009]
Income growth	-0.0381***	-0.0305***	0.007
	[0.009]	[0.009]	[0.011]
Fixed effects	Year & State	Year & County	Year & Zip
Observations	654,581	654,581	654,581
Adjusted R-squared	0.022	0.027	0.062

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability placebo models of store closures. All regressions include an intercept and year fixed effects. Models 1, 2, and 3 include state, county, and zip-code fixed effects, respectively. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

As can be seen in Table 2.9, the results are consistent with an externality effect. The coefficients on the lagged variables—β_1, β_2, and β_3—are identical to our baseline results in Table 2.7. The coefficient on the fourth variable—i.e. the forwarded

$\mathrm{n(same\ address)}_{i,t+1}$—is negative and significant in the first two models. However, once we move to the preferred specification which includes both year and zip-code fixed effects this coefficient becomes much smaller (-0.0022 in Column 3 as compared to -0.0060 in Column 1) and is no longer statistically significant. Further, the forwarded variables using the greater distance store closure counters are not statistically significant. Taken together the results show that the effect of store liquidation on subsequent store closures is not driven by the location of the retail chain-stores that will later become bankrupt but rather by the timing in which they were actually closed.

2.5.3 Stores closures inside shopping malls

Prior work has shown that anchor stores in shopping malls create positive externalities on other non-anchor stores by attracting customer traffic. Mall owners internalize this externality by providing rent subsidies to anchor stores. Indeed, the rent subsidy provided to anchor stores as compared to non-anchor stores—estimated at no less than 72 percent—suggests that these positive externalities are economically large. Given the importance of anchor stores within malls, we next focus our analysis on the potential externalities that arise when an anchor store in a shopping mall closes. To maintain our identification strategy, we focus only on the effects of anchor store closures that are a result of the liquidation of a national retail chain.

We match our data on retail chain stores to Esri's Major Shopping Centers, a panel dataset of major U.S. shopping centers that lists the name and address of each of the malls and includes data on gross leasable area in the mall, the number of stores, and the names of up to four anchor tenants in the mall. %Can we say something about how they define anchor stores?

There are 4,421 unique malls that are matched to 104,217 store-year observations. The average mall has a gross leasable area (GLA) of 474,019 square feet (median=349,437) and ranges from a 25th percentile of 259,086 sqf to a 75th percentile of 567,000 sqf. The matched malls span all of the fifty states and the District of Columbia. Figure 2.8 presents the geographical distribution of the malls that are matched to our data as well as the shopping mall gross leasable area.

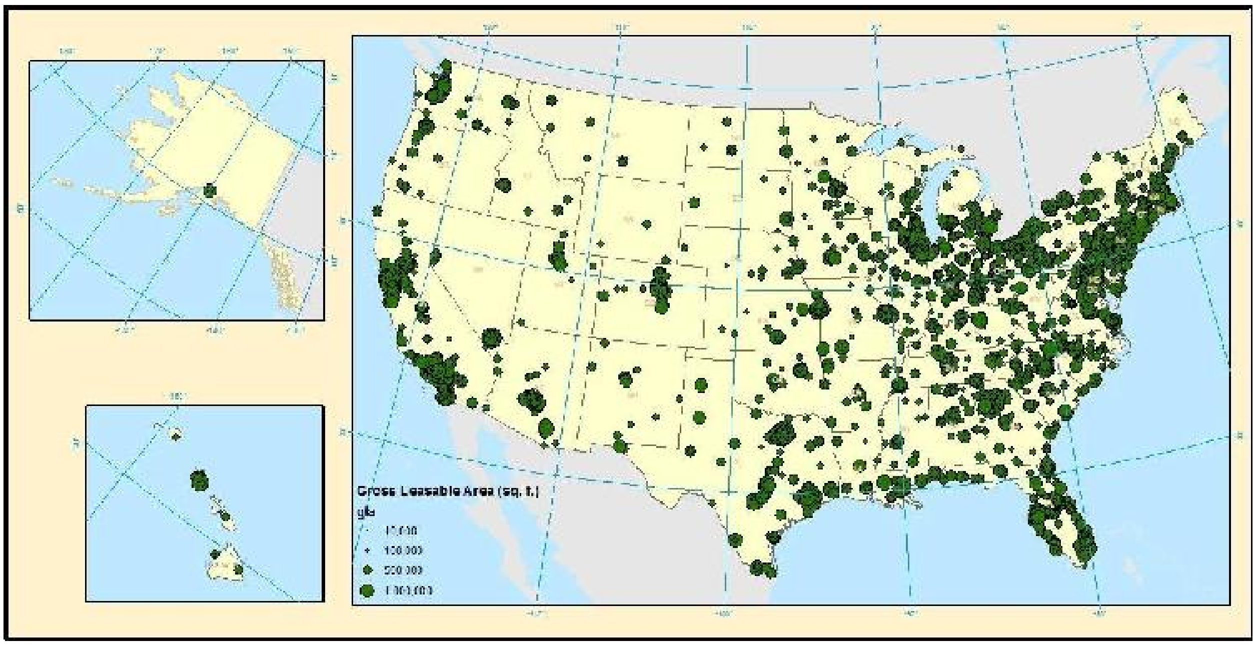

Figure 2.8: Shopping malls' locations and size

Next, to estimate the externality generated by store closures within malls, we rerun our baseline regressions only on stores that have been matched to the Esri Mall database. Similar to the baseline regressions, our main dependent variable in this regression, *same mall*, is simply the number of retail-chain stores in the mall that close due to the liquidation of the entire chain. Our data enable us to control for mall fixed effects (as opposed to just zip-code fixed effects) in addition to the year dummies which further alleviates concerns about the initial location of stores of chains that end-up in liquidation.

Table 2.10: Mall bankrupt stores and mall store closures

	(1)	(2)
Full liquidation bankrupt store closures$_{t-1}$		
same mall	0.003*	0.002
	[0.002]	[0.002]
same mall anchor store		0.009**
		[0.004]
Ln(income per household)	-0.046*	-0.048*
	[0.027]	[0.027]
Income growth	0.094**	0.095**
	[0.038]	[0.038]
Fixed effects	Year & Mall	Year & Mall
Observations	104,217	104,217
Adjusted R-squared	0.094	0.094

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of mall-based store closures. All regressions include an intercept and year and mall fixed effects. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

As Column 1 of Table 2.10 shows, we find that store closings within a mall lead to further store closures within a mall. When a store closes in a mall, the subsequent annual closure rate of other stores in the mall increases by 0.3 percentage points, or 4.9% of the sample mean. In Column 2 we add a second variable that counts the number of anchor stores within a mall that are closed as a result of the liquidation of a national retail chain. As the table shows, we find that most of the effect within malls is coming from anchor stores: The coefficient on *same mall* becomes insignificant while that on the number of national liquidating anchor stores rises to 0.009. The effect of anchor store closure is thus triple that of the average effect of non-anchor stores, consistent with prior research pointing to the impact of anchor stores in drawing in costumers. The economic effect is sizable with an anchor store closure causing a 14.7% increase in the probability of store closures within the mall relative to the unconditional mean.

One caveat that should be noted in regards to this effect is that some firms insert co-tenancy clauses into their lease contracts, which provide them the option to terminate their leases when certain stores close. Thus, the increase in the externality effect could be explained both by the greater importance of anchor stores in drawing traffic to malls, as well as the higher flexibility that fellow stores enjoy in terminating their leases when an anchor store closes.

In a separate set of regressions, we also analyze the effect of store closures on stores located outside malls. Table 2.11 repeats our baseline analysis in Table 2.7 for stores that were not matched to the Esri's Mall database. There are 550,364 stores in our data that are not part of matched malls. Such stores are either not located in shopping malls, or are located in smaller malls that are not matched to the Esri Mall database. As the table demonstrates, the coefficient on $\text{n(same address)}_{i,t+1}$ is positive and significant statistically indicating once again a negative externality of store closure on stores located in the same address.[13] Comparing the coefficients on the *same-address* variable in Table 2.11 to those in Table 2.10 indicates that the effect of store closure outside shopping malls on other stores located in the same address is similar to that of the effect of an anchor store closure.[14]

[13] Note that retail stores collocating in the same address could either be stores not in a mall but in the same building, or stores located in a mall which was not matched to the Esri database.

[14] Taking into account the standard errors of these coefficients shows that the coefficients are not statistically different for one another.

Table 2.11: Non-mall bankrupt stores and non-mall store closures

	(1)	(2)	(3)	(4)
Full liquidation bankrupt store closures$_{t-1}$				
same address	0.0115***	0.0118***	0.0115***	0.0087**
	[0.004]	[0.004]	[0.004]	[0.004]
distance $\leq$ 50 meters	-0.0015	-0.0013	-0.0008	-0.0034
	[0.003]	[0.003]	[0.003]	[0.003]
50 $<$ distance $\leq$ 100 meters	0.0053	0.0056	0.0060*	0.0039
	[0.004]	[0.004]	[0.004]	[0.003]
Ln(income per household)	0.0089***	0.0071***	-0.0023	-0.0682***
	[0.002]	[0.002]	[0.003]	[0.009]
Income growth	-0.0442***	-0.0491***	-0.0413***	0.0002
	[0.010]	[0.011]	[0.010]	[0.011]
Fixed effects	Year	Year & State	Year & County	Year & Zip
Observations	550,364	550,364	550,364	550,364
Adjusted R-squared	0.021	0.022	0.028	0.067

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of non-mall store closures. All regressions include an intercept and year fixed effects. Models 2, 3, and 4 include state, county, and zip-code fixed effects, respectively. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

One potential reason for this is that due to the small number of stores in small shopping malls or in buildings where stores collocate, any store closure will have a relatively large impact on other stores nearby.[15]

2.6 Heterogeneity in the response to store closures

In order to understand better the mechanisms through which store closures spread to further closing of stores, we add heterogeneity to our empirical analysis. In this section we investigate the transmission of negative externalities that are imposed by bankruptcies of neighboring stores further by studying the differential effect of store

[15] This also explains why the coefficient on *same address* is larger when focusing on stores not matched to malls than the sample-wide effect of *same address*. The latter effect includes the impact of non-anchor store closure within malls, which as Table 2.10 shows, is small.

closures along the following three peer characteristics: (i) across industries; (ii) conditional on a firm's financial strength; and (iii) store size.

2.6.1 The effect of bankrupt stores by industry

We begin by analyzing whether the effect of store closures on neighboring store closures depends on the industrial composition of stores in the same vicinity. Some spatial models of imperfect competition predict that firms will choose to locate as far from their newest competitors as possible (Chamberlin (1933), Nelson (1970), Salop (1979), Stuart (1979)). The key result of these models is that the further away other stores are from a particular store, the greater market power that specific store will have with respect to the consumers located near it. If so-called centrifugal competition is the main factor driving stores locations in the U.S., we should expect that store closures will benefit nearby stores that are in the same retail segment. This is simply because the remaining stores will end up facing less competition.

Alternative spatial models suggest that it may be optimal for stores in the same industry to locate next to one another. According to this view, the geographical concentration of similar stores is driven by consumers' imperfect information. For example, Wolinsky (1983, p. 274) writes:

> "[I]mperfectly informed consumers are attracted to a cluster of stores because that is the best setting for search. A store may thus get more business and higher profits when it is located next to similar stores. This effect may outweigh centrifugal competitive forces..."

Indeed, research in urban economics has provided a good deal of evidence for the existence of economies of agglomeration and industrial clusters.[16]

[16] See for example, Ellison and Glaeser (1999), Henderson et al. (1995), and Rosenthal and Strange (2003)).

To test how product substitutability and similarity influences the effect of retail store closures on neighboring retail stores, we use the North American Industry Classification System (NAICS) definition of an industry. To assign firms into industries, we employ two definitions that are based on 5-digit and 6-digit NAICS codes.

Specifically, for each store in our sample we define *same industry* analogs of n(same address), n($0 < distance \leq 50$), and n($50 < distance \leq 100$) which count only the number of liquidating retail-chain stores that are in the same industry of the given store, where industry identity is defined using either 5- or 6-digit NAICS. For each store, we also define *different industry* exposures to stores of liquidating national retail chains in an analogous manner. We then estimate, separately, the effect of *same industry* and *different industry* store closures on subsequent store closings in their area. Results that are based on 5-digit NAICS are presented in Table 2.12.

As the table shows, we find that the effect of *same industry* store closures is bigger than *different industry* store closures. In the specification that controls for year and zip-code fixed effects we find that the coefficient on n(same address) is 0.009 for *same industry* compared to 0.006 in the *different industry* regression. Moreover, we also find a positive and significant effect of our second distance measure, n($0 < distance \leq 50$), in the *same industry* regressions. This effect is quite sizable: the coefficient of 0.018 (significant at the 5 percent level) in Column 3 implies that the effect of having one store close increases the likelihood of further store closure by 29.5 percent relative to the unconditional mean for stores in the same industry and that are located within a 50m radius of the closing store. In contrast, as Columns 4-6 show, there is no effect of *different industry* n($0 < distance \leq 50$) on further store closures. We repeat the analysis using a 6-digit NAICS definitions and obtain very similar results.[17]

Table 2.12: Bankrupt stores industry and store closures (5-digit NAICS)

	(1)	(2)	(3)	(4)	(5)	(6)
Full liquidation bankrupt store closures **same** industry$_{t-1}$						
same address	0.008*	0.008*	0.009**			
	[0.004]	[0.004]	[0.004]			
distance ≤ 50 meters	0.022**	0.022**	0.018**			
	[0.009]	[0.009]	[0.009]			
50 < distance ≤ 100 meters	0.002	0.002	-0.004			
	[0.009]	[0.009]	[0.010]			
Full liquidation bankrupt store closures **different** industry$_{t-1}$						
same address				0.003**	0.004**	0.006***
				[0.002]	[0.002]	[0.002]
distance ≤ 50 meters				-0.001	-0.001	-0.004
				[0.002]	[0.002]	[0.003]
50 < distance ≤ 100 meters				0.003	0.002	0.001
				[0.003]	[0.003]	[0.003]
Ln(income per household)	0.005***	-0.005	-0.066***	0.005***	-0.005	-0.065***
	[0.002]	[0.003]	[0.009]	[0.002]	[0.003]	[0.009]
Income growth	-0.038***	-0.030***	0.007	-0.038***	-0.030***	0.007
	[0.009]	[0.009]	[0.011]	[0.009]	[0.009]	[0.011]
Fixed effects	Year & State	Year & County	Year & Zip	Year & State	Year & County	Year & Zip
Observations	654,581	654,581	654,581	654,581	654,581	654,581
Adjusted R-squared	0.022	0.027	0.062	0.022	0.027	0.062

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures. The table presents results for store closures in the same industry as well as store closures in different industries. All regressions include an intercept and year fixed effects. Models 1, 2, and 3 include state, county, and zip-code fixed effects, respectively. Models 4, 5, and 6 also include state, county, and zip-code fixed effects, respectively. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[17] These results are omitted for brevity and are available upon request.

2.6.2 Store closures and firm profitability

We further investigate the transmission of negative externalities that are imposed by bankruptcies of neighboring stores by studying the joint impact of a firm's financial health and neighboring store closures on the likelihood that a firm will close its own store. We hypothesize that the effect of neighboring store closures on the likelihood that a store will close should be larger for stores owned by parent firms that have low profitability. Less profitable firms are financially weaker, making them more vulnerable to a decline in demand that is driven by the reduction in traffic associated with neighboring stores closing down. We therefore introduce an interaction variable between profitability and each of the local store closures into the specification estimated in the regressions reported in Table 2.13.[18]

In Table 2.13 we run the analysis separately with different fixed effects to control for geographic heterogeneity. All regressions control for lagged values of firm size (natural log of book value of assets), leverage (defined as total debt divided by lagged assets), and profitability (EBITDA divided by assets). Column 1 of the table includes year fixed effects, Column 2 includes year and state fixed effects, while Columns 3 and 4 each control for year and either county or zip-code fixed effects. As in the rest of the analysis in the paper, standard errors are clustered at the zip code level.

As can be seen in Table 2.13, the coefficients on all three measures of bankrupt stores—n(same address), n($0 < distance \leq 50$), and n($50 < distance \leq 100$)—are positive and statistically significant, indicating that stores closed in large retail-chain liquidations lead to additional store closures in their vicinity. Consistent with the

[18] See Benmelech and Bergman (2011) for a similar approach.

Table 2.13: Bankrupt stores firm profitability and store closures

	(1)	(2)	(3)	(4)
Full liquidation bankrupt store closures$_{t-1}$				
same address	0.0329***	0.0332***	0.0345***	0.0364***
	[0.004]	[0.004]	[0.004]	[0.004]
× Profitability$_{t-1}$	-0.1679***	-0.1683***	-0.1709***	-0.1698***
	[0.016]	[0.016]	[0.016]	[0.016]
distance ≤ 50 meters	0.0110*	0.0116**	0.0109*	0.0066
	[0.006]	[0.006]	[0.006]	[0.006]
× Profitability$_{t-1}$	-0.0478*	-0.0485*	-0.0471	-0.0475
	[0.029]	[0.029]	[0.029]	[0.030]
50 < distance ≤ 100 meters	0.0227***	0.0233***	0.0241***	0.0205***
	[0.008]	[0.008]	[0.008]	[0.008]
× Profitability$_{t-1}$	-0.1085***	-0.1082***	-0.1123***	-0.1114***
	[0.037]	[0.037]	[0.037]	[0.038]
Size$_{t-1}$	-0.0067***	-0.0068***	-0.0067***	-0.0066***
	[0.000]	[0.000]	[0.000]	[0.000]
Leverage$_{t-1}$	0.1024***	0.1027***	0.1029***	0.1043***
	[0.003]	[0.003]	[0.003]	[0.003]
Profitability$_{t-1}$	0.0846***	0.0853***	0.0858***	0.0859***
	[0.006]	[0.006]	[0.006]	[0.006]
Ln(income per household)	0.0076***	0.0056**	-0.0027	-0.0899***
	[0.002]	[0.002]	[0.004]	[0.011]
Income growth	-0.0116	-0.0095	-0.0089	0.0415***
	[0.013]	[0.013]	[0.013]	[0.016]
Fixed effects	Year	Year & State	Year & County	Year & Zip
Observations	359,675	359,675	359,675	359,675
Adjusted R-squared	0.030	0.030	0.040	0.090

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures conditional on firm profitability. All regressions include an intercept and year fixed effects. Models 2, 3, and 4 include state, county, and zip-code fixed effects, respectively. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

prediction of the joint effect of financial distress and store closures, we find that the effect of local store closure is amplified when the retailer operating the neighboring store is experiencing low profitability. The coefficients on the interaction terms between each of the three distance measures and profitability is negative and significant suggesting that financially stronger firms can weather the decline in revenue that is caused by store closings in the area.

More specifically, the estimates imply that a local store closure increases the likelihood that a store in the same address with a parent firm in the 25th percentile of profitability will also close by 1.03 to 1.36 percentage points, which represent an increase of 16.9 to 22.2 percent relative to the unconditional mean. In contrast, when the parent of the store is in the 75th percentile of the sample profitability, the effect of of store closure on the likelihood of same-address store closure is not statistically different from zero.

Similar to the effect of store closures on same-address stores, the coefficient on the interaction term between $n(0 < distance \leq 50)$ and profitability is negative and statistically significant at the ten percent level (the effect ranges from -0.0471 to -0.0485) with standard errors of approximately 0.03) but only in the specification without county or zip code fixed effects.[19]

Finally, the coefficient on the interaction term between $n(50 < distance \leq 100)$ and profitability is negative and statistically significant in all specifications, including those with zip-code fixed effects. The magnitude of the coefficients indicate that a store closure 50 to 100 meters away increases the likelihood that a store with a parent in the

[19] Note, though, that the coefficient on the interaction term barely changes across all specifications.

25th percentile of the profitability distribution will close by 9.0 to 14.8 percent relative to the unconditional mean.

Moving to the firm-level variables, the results show that on average larger retailers are less likely to close their stores while more leveraged retailers are more likely to close their stores. Interestingly, we find that more profitable retailers are on average more likely to close their stores. One explanation for this finding could be that more profitable firms are more likely to experiment when choosing store locations, and hence are more likely to close stores which they find not to be profitable.

Taken together, our results show that stores of weaker firms are strongly affected by the closure of neighboring stores. The negative externality of store closure is greater on weaker firms than on stronger ones and, as Table 2.13 shows, the effect carries over larger distances. Stores of weaker firms thus seem to be more reliant on the existence of agglomeration economies. When these agglomerations are destroyed through the liquidation of neighboring stores, weaker stores are pushed towards economic inviability and shut down. Given an initial financial weakness in a geographic area, store closures can thus propagates across the area.

2.6.3 Store size and the effect of bankrupt stores

We continue by analyzing how store size affects the impact of store closures on the decision of neighboring stores to close. We hypothesize that a larger store will be more resilient to the closure of neighboring stores as compared to a smaller store since larger stores may be less reliant on neighboring stores to bring in costumer traffic. Further, to the extent that retailers act more quickly to shut down unsuccessful large stores as compared to unsuccessful small stores, for example, due to the greater impact larger stores have on retailers' bottom line, larger stores will on average be more profitable than smaller ones. Similar to the results in the prior section, we would then expect larger stores to be more resilient to local store closures.

Table 2.14: Store size and store closures

	(1)	(2)	(3)	(4)
Full liquidation bankrupt store closures$_{t-1}$				
same address	0.058***	0.059***	0.060***	0.050***
	[0.009]	[0.009]	[0.009]	[0.010]
× Store size	-0.014***	-0.014***	-0.014***	-0.012***
	[0.002]	[0.002]	[0.002]	[0.002]
distance ≤ 50 meters	-0.007	-0.007	-0.006	-0.010
	[0.010]	[0.011]	[0.011]	[0.011]
× Store size	0.003	0.003	0.003	0.003
	[0.003]	[0.003]	[0.003]	[0.003]
50 < distance ≤ 100 meters	-0.001	-0.001	0.001	-0.001
	[0.009]	[0.009]	[0.009]	[0.009]
× Store size	0.000	0.000	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]
Store size	-0.004***	-0.004***	-0.004***	-0.005***
	[0.000]	[0.000]	[0.000]	[0.000]
Ln(income per household)	0.000	-0.001	-0.007*	-0.023
	[0.002]	[0.002]	[0.004]	[0.014]
Income growth	0.032**	0.029*	0.027*	0.037**
	[0.015]	[0.015]	[0.015]	[0.015]
Fixed effects	Year	Year & State	Year & County	Year & Zip
Observations	181,066	181,066	181,066	181,066
Adjusted R^2	0.016	0.017	0.030	0.121

Notes: This table presents coefficient estimates and standard errors in parentheses for linear probability models of store closures conditional on store size. All regressions include an intercept and year fixed effects. Models 2, 3, and 4 include state, county, and zip-code fixed effects, respectively. Standard errors are calculated by clustering at the zip code level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We rerun our baseline regressions analyzing the likelihood of store closure while interacting store size, as measured by the number of employees in each store, with each of the three local store closure variables, n(same address), n($0 < distance \leq 50$), and n($50 < distance \leq 100$). We add the usual set of control variables which include the host of year and geographic fixed effects. The results are reported in Table 2.14.

As can be seen in the table, we find a negative coefficient on the interaction term between store size and the n(same address) variable which measures the number of store closures of liquidating national retail chains in a given address. Consistent with our hypothesis, the negative coefficient on the interaction term implies that larger stores are indeed less affected than smaller ones by the closure of stores located in the same address. The economic effect is sizable: Focusing on the specification with zip-code fixed effects, following the shutdown of a neighboring store, a store in the 25th percentile of the size distribution experiences a 47 percent rise in the probability of closure relative to the mean. In contrast, a store in the 75th percentile of the size distribution experiences only a 8.2 percent rise in the probability of closure. The data thus support the hypothesis that larger stores are more resilient to neighboring store closures and less reliant on agglomeration economies to generate traffic.

2.7 Conclusion

Most empirical work on agglomeration economies focuses on the creation of economies of agglomeration through the endogenous choice of firm entry. In this paper, rather than focusing on the endogenous creation of agglomeration economies we study how downturns damage economies of agglomeration.

Our analysis shows that bankrupt firms impose negative externalities on non-bankrupt neighboring firms through the weakening of retail agglomeration economies. Store closures naturally lead to reduced attractiveness of retail areas as customers prefer to shop in areas with full occupancy. This, in turn, leads to declines in demand for retail services in the vicinity of bankrupt stores, causing contagion from financially distressed companies to stores of non-bankrupt firms. We argue that in downturns agglomeration economies may propagate bankruptcies and financial distress.

Chapter 3

Beyond the Corner Office:

Employee Characteristics and Bank Performance

3.1 Introduction

In this paper, I investigate whether characteristics of bank employees shed light on bank conduct and performance before and during the financial crisis. While previous studies have considered top executives' characteristics and their impact on firm performance,[1] virtually no attention has been paid to the characteristics of non-executives.[2] My paper is the first to do a close study of the individual characteristics of a firm's workforce as a whole in efforts to understand performance.

To this end, I use a novel data set created by merging 1) individual-level resume data from a major professional networking website and 2) bank-level performance and balance sheet data from Call Reports and CRSP.[3] The advantage of my dataset of individual resumes is that it allows me to reconstruct snapshots of workforces and their

[1] See, for example, Bertrand and Schoar (2003), Malmendier and Tate (2005), Güner, Malmendier, and Tate (2008), Kaplan, Klebanov, and Sorensen (2012), Graham, Harvey, and Puri (2013), Minton, Taillard, and Williamson (2014), and Benmelech and Frydman (2015).

[2] Some exceptions are Agarwal and Wang (2009), Hertzberg, Liberti, and Paravisni (2010), Berg, Puri, and Rocholl (2013), Tzioumis and Gee (2013), Agarwal and Ben-David (2014), and Cole, Kanz, and Klapper (2015). These studies are either experimental over a subset of banks' employees or use proprietary data from a single lender.

[3] I supplement the main dataset used in the baseline analysis with the information on geographic distribution of banks' deposits from FDIC's Summary of Deposits, house prices from Zillow, and the Risk Management Index from Ellul and Yerramilli (2013).

characteristics in the 224 bank holding companies (BHCs) in my sample.[4] I am able to observe how the workforces of banks evolved in the pre-crisis years and document the relationship between a variety of workforce measures (particularly employee education, experience, and stability of employment) and crisis performance.

In my analysis, I use several measures of bank performance, including stock returns, bank failure, and percentage of loans charged-off (overall and by loan category). I focus on four workforce measures: 1) percentage of employees with an MBA; 2) percentage of employees who received a degree from a highly-ranked university; 3) percentage of employees with a high propensity to switch jobs in the past; and 4) average turnover of the workforce.[5,6] I hone in on these four characteristics because extant literature has documented a relationship between such traits at the executive level and firm performance. For instance, Bertrand and Schoar (2003) note that employees with MBAs appear to follow more aggressive strategies and Minton, Taillard, and Williamson (2014) find that financial expertise amongst directors is strongly related to lower performance during crisis. Perez-Gonzalez (2006) finds that family-appointed CEOs with degrees from selective academic institutions tend to outperform those without them. Berger, Kick, and Schaeck (2014) find that younger executive teams tend to be riskier; and Chernenko, Hanson, and Sunderam (2015) find that experience was a significant predictor of crisis performance, as inexperienced managers had almost twice as much subprime exposure as their seasoned counterparts.

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[4] FDICs Summary of Deposits contains matching between BHCs and their commercial bank subsidiaries. I use it to aggregate commercial banks to the BHC level.

[5] Turnover is defined as the negative of the average job tenure of a bank's employees.

[6] These variables are labeled in the regression tables as *MBA*, *Top school*, *Job jumper*, and *Turnover*, respectively.

Job mobility measures have received less attention in the finance literature because of their reliance on employer-employee matched data. The broader economics literature has explored the effects of job mobility on individual outcomes such as wage growth (Keith and McWilliams 1999, Altonji and Williams 2005) and has found positive wage effects for seniority, suggesting that workers acquire firm-specific human capital for which they are compensated.[7] Individuals with a tendency to move jobs despite this added compensation plausibly 1) have a preference for finding novel job opportunities or 2) tend to get laid off by employers. It is natural to postulate, then, that a workforce with a documented predisposition to move jobs for either reason will be less stable and require excessive future investment in worker training. As such, I anticipate that job jumping will be negatively related to performance.

I find that banks with a higher proportion of workers having the aforementioned traits (MBAs, top school degree holders, job jumpers, and high turnover) tended to perform worse in the crisis than their counterparts. A one-standard deviation increase in the proportion of MBAs lowers the bank's stock return during the recent crisis by 4.5 percentage points. Similar statistics for the fraction of top school degree-holders, job jumpers, and worker turnover are 9.4, 12.2, and 13.5 percentage points respectively.[8] I also show that these same workforce measures are positively related to bank failure as well as the fraction of loans charged-off in the crisis years.

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[7] In fact, early-career wage growth is strongly associated with higher job mobility of young employees (Topel and Ward 1992), but frequent job switching over the entire course of one's career is associated with lower earnings (Fuller 2008).

[8] These workforce measures are aggregated to the bank level and adjusted by bank size.

I use a host of observable bank characteristics (for example, pre-crisis growth, securitization activity, compensation, and composition of the loan portfolio)[9] known to be related to performance and risk-taking to show that my workforce measures are not proxies for other commonly used indicators of banks' vulnerability to crisis. The baseline relationship between crisis performance and workforce measures is virtually unchanged in the presence of additional controls. I also show that the relationships between the workforce measures and different bank characteristics are, by and large, flat. Accordingly, my workforce measures are unlikely to be picking up the effect of some known measures of banks' vulnerability to crisis. Rather they provide meaningful information orthogonal to that which can be derived from other observable traits.

These baseline results lead me to develop three hypotheses about the nature of the relationship between my workforce measures and bank performance during crisis that I can then take to my data.

My first hypothesis is that firms with higher proportions of MBAs, top school employees, job jumpers, and workers with relatively short tenures[10] had such workforce compositions because they looked to grow aggressively in the pre-crisis period, and these were the types of workers that were available to hire. If this is the case, then the

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[9] The full list of variables includes: pre-crisis stock returns volatility, tier-1 capital ratio, ratio of core deposits to assets, housing bubble exposure, securitization activity, ratio of private MBS to assets, assets growth, assets per employee growth, number of employees growth, ratio of loans to assets, fraction of non-interest income in total income, assets per employee, residual compensation, fraction of real estate loans in total loans, fraction of C&I loans, fraction of consumer loans, fraction of agricultural loans, fraction of other loans, and Herfindahl index for loan categories.

[10] I define my *turnover* variable as the negative of average job tenure. I choose to work with *turnover* for expositional convenience so that all of my workforce measures move in the same direction. That is, high values of MBA, top school, job jumper, and turnover are all associated with poor performance in crisis.

relationship I document between these measures and performance can be explained by pre-crisis hiring.

I reject this hypothesis by showing that the characteristics of pre-existing employees—those recruited before the pre-crisis expansion kicked off—are driving the relationship I document between crisis performance and workforce measures. In other words, the hiring implemented by banks to accommodate the growth that preceded the financial crisis does not explain the baseline relationship between how well or poorly banks performed in crisis and the composition of their workforces.

My second hypothesis is that the relationship between workforce characteristics and bank performance is attributable to underlying bank quality. If this is the case, I expect some banks to always perform poorly—in booms and busts alike—and some banks to consistently perform well. I reject this hypothesis by showing that the workforce measures related to poor crisis performance are, if anything, indicative of superior performance in the pre-crisis period.[11,12]

My third hypothesis is that my workforce measures are related to risk-taking by banks. If this is the case, then I would expect that risk-taking will be highest in banks with the highest proportion of MBAs, top school graduates, high turnover employees, and job jumpers. I find support for this hypothesis in the data.

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[11] This finding is consistent with Beltratti and Stulz (2012) who show that banks that perform worst in crisis had above-average returns before the crisis.

[12] I also show that banks that had the largest proportion of MBAs, top school degrees, job jumpers, and workers with the shortest tenures had higher compensation per employee than their counterparts.

I measure risk by calculating holdings of highly rated securitization tranches that are not government or agency affiliated,[13] computing the ratio of private mortgage-backed securities to assets, and calculating the average interest rate on loans. I find that banks with the highest proportion of MBAs, top school graduates, high turnover employees, and job jumpers took on more risk before the crisis. They also had higher volatility of stock returns and higher realized tail risk[14] which is consistent with their taking more ex-ante risk that resulted in greater ex-post fluctuations of stock prices. Finally, these banks perform more poorly on Ellul and Yeramilli's (2013) risk management index,[15] which assesses the strength of risk management functions at bank holding companies. Taken together, these findings are consistent with the hypothesis that my workforce measures are related to banks' crisis performance because of differences in banks' risk-taking before the crisis.

Given the role that the real estate boom played in the financial crisis,[16] it is also important to consider its role in my study of human capital and bank performance during the Great Recession. I measure a bank's exposure to the housing bubble as the

[13] I follow Erel, Nadauld, and Stulz (2014) who study holdings of highly rated tranches, which are highly rated securities issued in securitizations and held on BHC balance sheets, like subprime residential mortgages and collateralized debt obligations. They identify the amount of securities assigned an AA or AAA risk weight that are not government or agency-affiliated, and call this the "highly rated residual."

[14] I compute tail risk following Acharya et al. (2010) based on the stock's average return over its 5% worst trading days.

[15] To construct a risk management index (RMI), Ellul and Yerramilli (2013) hand-collect information on the organizational structure of the risk management function for each bank holding company from its 10-K statements, proxy statements, and annual reports. Their measure is only available for a subset of the banks in my sample.

[16] Mian and Sufi have written extensively on the role of housing in the recent crisis and in downturns generally. See, for example, Mian and Sufi (2009), Mian and Sufi (2010), and Mian and Sufi (2011).

deposit-weighted average of the growth in median home prices for each state in which the bank has branches.[17,18]

As expected, I find that banks with more exposure to the housing bubble fare worse in the crisis. Consistent with the notion that my workforce measures are not proxies for other known observable characteristics, the predictive powers of my workforce measures are not affected by adding controls for exposure to the real estate bubble. Interestingly, I find that the relationship between my workforce measures and the *form* of risk-taking undertaken by banks depends on the growth of home prices in banks' locations. In particular, banks located in states with booming pre-crisis real estate prices—like Nevada—take more risk pre-crisis through risky loan origination and securitization; whereas banks in states with sluggish pre-crisis home prices growth—like Iowa—take more risk by holding real estate-backed securities on their books.[19]

Beyond housing bubble exposure, it is possible that some aspects of local labor markets, such as the availability of MBAs in the pool of potential hires,[20] is driving the results I observe between bank performance and workforce characteristics. I reject this theory by demonstrating that the relationship is not driven by state averages of these workforce measures but rather is strongly related to the workforce composition of the

[17] An important caveat is that the locations of bank branches are endogenous. It is feasible that banks willing to have high exposure to the housing boom proactively set up locations and attracted deposits in areas with rising real estate prices.

[18] Garmaise (2013) mentions that medium-sized banks are typically local mortgage lenders.

[19] Examples include highly rated securitization tranches and private mortgage-backed securities.

[20] Oyer and Schaefer (2012), for example, study firm-employee matching in the context of law firms and find that geography/proximity to a specific law school is an important factor.

individual bank under consideration. This suggests that the matching of employees to banks on bank's strategy—and not on bank's location—underpins my empirical findings.

Additionally, I explore the relationship between banks' performance and the characteristics of employees with different job functions. If it is risk-taking that is driving the relationship I document between performance and my workforce measures, then I expect that those individuals with job descriptions related to risk-taking activities—referred to in my analysis as "employees with impact"—are the drivers of the results I document.[21] I find evidence to support this notion.

Finally, to generalize my results, I extend my analysis to the 1998 crisis and find that bank performance during the crisis could be predicted by the same workforce characteristics I study in the context of the Great Recession.[22] Additionally, I replicate the results of Fahlenbrach et. al (2012)[23] in my sample and show that performance in the 1998 crisis is a powerful predictor of performance in the most recent crisis. However, the workforce measures I study, calculated as of year-end 1997, are stronger predictors of recent financial crisis performance. This is consistent with the proposition that the persistence of banks' vulnerability to crisis stems from the persistence of their workforce characteristics.

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[21] This is similar in spirit to Adams, Almeida, and Ferreira (2005) who show that companies run by CEOs with impact (with influence over crucial decisions) have more volatile stock returns.

[22] This is a noteworthy result. The 1998 crisis and the Great Recession happened for very different reasons and occurred almost a decade apart. Yet, I find that the same workforce measures that predict poor performance in the recent financial crisis were related to subpar performance in the 1998 crisis. As I argue later in the paper, this result advocates for an interpretation of my workforce measures as indicative of latent firm culture or business strategy.

[23] Fahlenbrach et al. (2012) demonstrate that a bank's stock return during the 1998 crisis predicted both its stock return and its probability of failure in the recent financial crisis. The authors conclude that their "findings are consistent with persistence in a bank's risk culture and/or aspects of its business model that make its performance sensitive to crises."

Taken together, my results suggest that workforce measures could help quantify components of banks' risk cultures or business strategies that contribute to financial institutions' vulnerability to crisis.

Banks' risk-taking is a multi-dimensional object that is hard to capture with a single measure. Banks differ in their holdings of safe and risky assets, in the liquidity of assets on their balance sheets, in the growth rates of their loan portfolios, in the maturity mismatch between assets and liability, and the like.[24] It is challenging to parsimoniously account for the full spectrum of banks' risk-taking activities. My study offers a way to reduce the dimensionality of the problem by focusing on the characteristics of banks' workforces.

There are two distinct channels that could result in a relationship between individual characteristics and firm performance: 1) individuals with certain characteristics could be hired to act in accordance with an overarching business strategy or corporate culture; or 2) firms' hiring of particular employees could result in employees making decisions that impact banks' paths to success. This paper takes no stand on which of these mechanisms is at play, though it is likely that some combination of the two drives the relationship I document between workforce characteristics and bank performance.

Consider an example from my dataset to help illustrate these empirical findings. As of 2006, Corus Bank had the highest fraction of employees with MBA degrees from top schools of all the bank holding companies in my sample. Headquartered in Illinois, it

[24] See Falato and Scharfstein (2015) for a comprehensive discussion of banks' risk-taking behavior.

did incredibly well before the crisis.[25] Investment in its stock at the beginning of 2003 earned more than 100% by the end of 2006. The bank failed in September of 2009, and its failure received a fair amount of attention, both in the crisis and its aftermath. Chicago Real Estate Daily labeled it a "national poster child for reckless risk-taking" and a Treasury Audit Report in 2012 concluded that Corus Bank made a series of poor investments, including Florida developments "surrounded by car dealerships instead of water."[26,27]

This example is not unique—it is a pattern I observe time and time again in my analysis. Having controlled for commonly used determinants of performance, the workforce characteristics of banks are highly related to bank outcomes in crisis, and the same characteristics that seem to be related to poor performance during the crisis are related to above par performance in the pre-crisis period.

This paper builds on and contributes to three distinct strands of extant finance literature. Past work on the personal characteristics of C-suite executives and board members has linked individual characteristics to corporate performance and has found that variation in their levels of financial expertise (Güner, Malmendier, and Tate 2008; Minton, Taillard, and Williamson 2014); education (Bertrand and Schoar 2003); and other individual characteristics like military service (Benmelech and Frydman 2015);

[25] In fact, the Corus Bank's stock was doing so well that it was split 2-for-1 twice: in December 2003 and May 2006.

[26] The full excerpt from the report reads: "OCC officials told us that the quality of management's decisions declined in 2007 and 2008 as evidenced by some projects Corus chose to finance. For example, Corus originated a loan for a development that was 5 to 10 miles off the Las Vegas strip. Similarly, an OCC official stated that the bank's projects in later years were not as high quality, citing Florida developments surrounded by car dealerships instead of water. Another OCC official also said the locations of the bank's projects in Florida did not make sense, such as a project in the Everglades."

[27] The lengthy investigation into specific actions that led to the bank's demise is suggestive of some elements of risk-taking being hard to observe—let alone quantify—especially ex-ante.

overconfidence and optimism (Malmendier and Tate 2005; Graham, Harvey, and Puri 2013) and general ability, communication, and execution skills (Kaplan, Klebanov, and Sorensen 2012) impacts firm performance.

My paper pushes the literature in this field forward by moving beyond the study of top-level executives to consider the characteristics of *all* the employees of a firm and how these relate to firm success. Earlier work on the role of non-executives at financial institutions has been mostly experimental and limited in scope. Some studies have conducted experiments with commercial bank loan officers to test how compensation affects risk taking (Cole, Kanz, and Klapper 2015; Agarwal and Wang 2009; Agarwal and Ben-David 2014). Others have used proprietary data from a single lender (Hertzberg, Liberti, and Paravisni 2010; Berg, Puri, and Rocholl 2013; Tzioumis and Gee 2013). The only large sample study that looks to move beyond the study of top executives is a recent paper by Acharya, Litov, and Sepe (2014) that introduces measures of non-executive incentives and shows that these played a role in promoting risk-taking by banks during the crisis.

My paper provides direct evidence on the relationship between the characteristics of all of a bank's employees and performance. By expanding the study of the firm beyond the C-suite and to the workforce as a whole, my study also contributes to the incipient literature on the role of corporate culture (Cohn, Fehr, and Maréchal 2014; Lo 2015). Although past work in this arena has sought to quantify corporate culture using survey data (Guiso, Sapienza, and Zingales 2015), my paper proposes an alternative lens through which one can infer a bank's corporate culture—namely, by examining the personal characteristics of its employees.[28]

Finally, I build on the literature that has sought to understand bank performance and risk-taking during the crisis. My results are consistent with Fahlenbrach et al. (2012); Ellul and Yerramilli (2013); Rajan (2010); and Cheng, Hong, and Scheinkman (2015)—all of whom document a relationship between risk-taking and crisis performance. I contribute to this literature by demonstrating that examining the workforce composition of banks sheds light on risk-taking behavior and provides a powerful predictor for how banks will fare in an epoch of crisis.

The remainder of the paper is organized as follows. Section 3.2 introduces the data sources and variables. Section 3.3 establishes the baseline effect relating workforce characteristics and bank performance. Section 3.4 develops potential hypotheses to explain the baseline result; they are evaluated in Section 3.5. Section 3.6 explores how workforce characteristics and exposure to the housing bubble affect forms of risk-taking. Section 3.7 considers how local labor markets are related to my results. Section 3.8 uses textual job descriptions to ascertain that the results are driven by employees that impact risk-taking. Section 3.9 extends the analysis to the 1998 crisis. Section 3.10 concludes.

3.2 Data

I examine employee-level data in banks and document a relationship between workforce characteristics and firm performance. In order to study this relationship, I merge data from different sources: 1) individual resume data from a major professional

[28] See Zingales (2015) for a discussion of papers on corporate culture contributing to the incipient "cultural revolution" in finance.

networking website; 2) bank-level data from CRSP, Call Reports, and the FDIC's Summary of Deposits as well as the risk management index (RMI) from Ellul and Yerramilli (2013);[29] and 3) data on home prices from Zillow, an online real estate database that tracks real estate valuations throughout the United States.

3.2.1 Bank-level data

My initial bank sample includes all bank holding companies for which Call Reports have balance sheet information over the pre-crisis period, from 2004–2006. I further restrict my sample to those BHCs with stock price returns available on CRSP over the financial crisis period of 2007–2008.[30]

The FDIC's Summary of Deposits contains the by-branch distribution of a bank's deposits. I supplement it with Zillow home prices data to estimate the exposure of each bank to the housing bubble. I do so by constructing a measure of deposit-weighted home price growth for all states where a bank has branches.[31]

I also use the RMI of Ellul and Yerramilli (2013) which measures the importance each BHC attaches to the risk management function. This index reflects the organizational structure of risk management as detailed in banks' 10-K statements, proxy statements, and annual reports.

In my analysis, I use stock returns between July 2007 and December 2008 as measures of crisis performance, as well as bank failure and fractions of loans charged-

[29] I thank Andrew Ellul and Vijay Yerramilli for sharing their RMI data.

[30] I use *CRSP-FRB Link* file by Federal Reserve Bank of New York (2014) to match BHCs from Call Reports to CRSP.

[31] In the analysis in this paper, I use bank branches as of 2006. My results are robust to the use of branch information from earlier years.

off.[32] I follow Fahlenbrach et al. (2012) in choosing control variables for the performance regressions. In particular, I use the book-to-market ratio, equity beta, and leverage. My sample consists of both large and small banks—I control for size using fixed effects for quintiles of banks' total assets.[33]

3.2.2 Data on individuals

My individual-level human capital data was obtained from a major professional networking site in 2015. First, I matched bank holding companies in the sample to their subsidiary commercial banks—I used the FDIC's Summary of Deposits as of 2006 for this purpose. Second, I identified individuals that list the names of banks on their resumes.[34] Since I observe the start and end dates of jobs, I can infer the composition of the workforce of each BHC as of any date by looking at employees that were hired by that BHC—or one of its commercial bank subsidiaries—before that date and either left that job after that date or are still employed at that bank. I end up with just over 250,000 people employed in at least one of the 224 bank holding companies in my sample at some point between 1997 and 2006.[35] For each individual, I observe career trajectory and educational background.

[32] In focusing on this time period, I follow Fahlenbrach et al. (2012) who stop calculating buy-and-hold returns in December 2008 in their analysis because, even though the crisis definitively did not end in 2008, losses in 2009 were at least partly affected by banks' probabilities of being nationalized. My results hold when I instead calculate returns through 2009.

[33] Using fixed effects for quintiles of banks' assets size is a more restrictive way to control for size, as it is agnostic with respect to the functional form.

[34] In situations when two or more bank holding companies have commercial banks with similar names, it is challenging to determine the institution where an individual is actually employed. To minimize measurement error, cases like these are dropped from the sample.

[35] The professional networking platform I study in this paper did not exist in 1997. As such, I rely on information that individuals retroactively filled out when they created their pages.

Individuals utilize this professional platform in order to network with potential employers and collaborators. As of 2015, there are over 300 million members worldwide and over 100 million members in the United States alone. While the membership of this networking website does not constitute a nationally representative sample, it is fairly complete for professionals and the size of the platform makes its users and their characteristics ripe for empirical investigation. In particular, the use of professional networking platforms is especially common in fields like finance, lending additional credence to my working with this individual-level data in this context.

My paper makes use of individual resume-data on a large scale. Past studies that considered professional networking data on individual resumes (e.g., Cheng et al. 2014; Gompers et al. 2015) used it to supplement their analyses with the backgrounds of specific executives. In another application, Brown and Matsa (2016) examine the resume-data of job applicants to financial firms in times of distress. In contrast to the prior literature, I look at the entire universe of firm employees and do not solely focus on the characteristics of a few specific individuals at particular moments in time.

I focus on four individual characteristics derived from the resume data I collect: 1) having an MBA degree; 2) having a degree from a top 50 university;[36] 3) having a propensity to change jobs more frequently than a median employee with similar career length; and 4) job turnover, defined as the negative of current job tenure. For my

[36] I use the U.S. News & World Report's rankings of universities.

analysis, I aggregate these variables to the bank level. Then, I adjust those bank level averages for banks' size and standardize them.[37]

My variables are chosen to satisfy two objectives. First, they must be relevant for my question and thus contain information that could plausibly be related to individual employees' contributions to bank performance. Thus, they must bear some relation to individual skills or bank technology or strategy. Second, the workforce characteristic variables must be well defined for as many people in my sample as possible. The power of my dataset of individual resumes lies in its size—over 250,000 unique person-level observations. As one would expect, there is of course a tradeoff between making the workforce variables relevant to the question at hand and being able to specify them for as many individuals in my sample as possible. For example, one potential variable of interest is college major.[38] Particularly, I would have liked to focus on those employees who did undergraduate coursework in finance, mathematics, and economics, as they exhibited both interest in and exposure to areas of science that could be useful, especially in non-traditional banking. However, in my sample less than 50% of individuals list their majors. I would thus not be able to utilize half of my person-level observations in such analysis. There would also be substantial noise in this variable, as focusing on those individuals who list themselves as having a financially relevant undergraduate major may drastically underreport the number of individuals in my sample who have this characteristic. Thus, I encounter a challenge in honing in on

[37] The size-adjusted characteristic is a residual from the regression of raw bank-level averages on the fixed effects for quintiles of banks' assets. Unless otherwise specified, when I refer to my workforce characteristic measures, I have in mind the size-adjusted standardized variables.

[38] I could classify the employees in my sample into categories based on the coursework they were most exposed to in their collegiate years—by science major (e.g., math, physics, computer science), economics major (e.g., business, management, finance), or humanities (e.g., literature, philosophy, history).

variables that will both be informative and somewhat reliably self-reported on this professional networking site.

I focus on the workforce variables MBA, top school degree, job jumper, and job turnover because I believe they best manage the aforementioned tradeoff. Particularly, they are both relevant to the question of how individual characteristics can be informative on bank performance and likely to be correctly reported by a large proportion of the individuals in my sample. I discuss the merits of these variables in turn below.

3.2.2.1 MBA

First, my MBA variable meets both the criteria outlined above. Previous research has considered the importance of MBAs in the finance industry. MBAs have traditionally been considered to have the financial expertise necessary to undertake complicated bank strategies.[39] Bertrand and Schoar (2003) show that top executives with MBA degrees tend to follow aggressive strategies. Malmendier and Tate (2005) find that CEOs with financial education tend to exhibit lower investment-cash flow sensitivity. In a different but still relevant context, Grimm and Smith (1991) find that having a senior management team with a higher proportion of MBAs made railroads more likely to change strategy in the wake of the deregulation of the railroad industry.

Anecdotally, there is also a sense that MBA programs teach sophisticated financial techniques that will be relevant to employees' ability to contribute to firm performance. This is why students are willing to bear the burden of both the financial

[39] The fraction of MBAs is traditionally high in financial firms with businesses demanding a high level of financial sophistication. For example, the fraction of partner level executives with an MBA is 57% in the sample of 79 private equity firms in Gompers et al. (2015).

and opportunity cost necessary to expend two years in these professional degree programs.

MBA degree is also the least noisy of the education variables that I am able to measure. Individuals typically get MBA degrees in order to help transition careers and gain skills relevant to their future employment, and thus it is natural to disclose information about these degrees on their resumes.

Within MBAs, I specifically assign a value of "1" to those individuals who report receiving an MBA. For an average bank in my sample, 16.3% of bank employees report having an MBA degree.

3.2.2.2 Top school

There are two possible avenues through which holding a degree from a top academic institution may be related to firm performance. Theoretically, employers are drawn to employees based on some (hopefully observable) indicator of their ability. One possibility is that individuals with elite degrees have acquired human capital through their selective education that will be relevant to how the firms that employ them perform. Alternatively, following Spence (1974), employees may be sending a signal to employers of their potential by acquiring impressive educational credentials. I am unable to tease out which mechanism is at play.

Although virtually no work has been done on understanding the elite education of the workforce as a whole and its impact on firm performance, some limited work has been done in narrow contexts and it motivates our reliance on this measure. First, Palia (2000) provides support for the notion that the executive labor market slots managers with higher education quality into jobs where their human capital will have higher returns, explaining why CEOs with lower quality education tend to be employed in highly regulated industries with little room for them to creatively maneuver and make use of their educational background. Additionally, Perez-Gonzalez (2006) finds that when a family-owned firm is managed by a CEO without top education credentials, this firm performs poorly relative to a family-owned firm managed by a well-educated CEO; providing evidence against nepotism and in favor of an executive's education as predictive of her firm's performance. In a slightly different context, Cohen et al. (2010) find evidence that sell-side analysts' educational background is relevant to the performance of their predictions. And Gompers et al. (2016) show that venture capitalists with top school degrees have a higher fraction of successful exits.

Like my MBA variable, the top school variable is valuable because it allows me to build on past literature that has considered the role of educational backgrounds in firm performance. Although past work has been able to consider the education of top executives, my dataset affords me the opportunity to create snapshots of the educational background of the workforce as a whole and determine how these measures can provide information about a firm.

For the top school variable, I specifically assign a value of "1" to those individuals who report receiving a degree from a top 50 academic institution.[40] For an average bank in my sample, 10.2% of bank employees report having a degree from a top school.

[40] Top school in my sample refers to the top 50 schools in the U.S. News and World Report ranking. This is a rather arbitrary cutoff, and I could have looked at a smaller (i.e. top-25) or larger (i.e. top-100) group, and my results would have been substantively the same.

3.2.2.3 Job jumper

My third resume variable is a measure of the propensity of employees to change jobs. An individual is classified as a job jumper if she has had more jobs than a median person with the same career duration.[41]

This measure can be interpreted in multiple ways. One plausible story is that stable workplaces (few job jumping employees) have a culture of promoting internally, and those with significant job jumping tend to hire outside talent—thus, this job jumping variable is a proxy for workforce culture, with banks with many job jumpers being less likely to nurture talent internally. Another feasible interpretation is that the propensity to job jump is an inherent characteristic of a particular worker, who tends to move jobs and values what she perceives as short term-gains over stability.

My job jumper variable captures the job mobility of individuals, which has been long discussed in the labor economics literature in the context of human capital functions and the returns to seniority for workers.[42] In the finance literature, such variables have rarely been utilized because of data limitations. However, because my resume-level data allows me to see reported current and past employment, I am able to capture the job mobility of individuals. There are two channels through which job jumping could conceivably be relevant to firm performance. In the first extreme case,

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[41] I assign individuals into 5-year experience cohorts based on the duration of their career (since college graduation or since the first job when college graduation year is unavailable). Then I calculate the median number of past jobs for each cohort. Individuals who have had more jobs than the median of their experience cohort are classified as job jumpers.

[42] E.g., Topel and Ward (1992) study the job mobility of young men and find that job changing is critical to workers' movement toward stable employment; Farber (1999) finds that worker heterogeneity and firm specific capital are significant factors in accounting for differential worker mobility patterns; Altonji and Shakotko (1987) discuss the effects of firm tenure on earnings; Altonji and Williams (2005) reassess whether wages rise with seniority; Jovanovic (1979) models firm-specific capital and its impact on worker turnover; and Buchinsky et al. (2010) model the joint decisions of participation and job mobility to ascertain the return to seniority in the United States.

where all the individuals who make use of this professional networking platform report all employment, irrespective of its length, job jumper captures those individuals who have the greatest tendency to move between jobs. In this case, job jumping is relevant because it captures individuals' tendency to take on personal risk, or perhaps the tendency of certain banks to be willing to hire individuals who are less likely to display strong attachment to their firm. In the second extreme, where everyone has roughly the same number of jobs, but some have a predisposition to report all employment, no matter its length, and others are more reticent in reporting their experiences; job jumping is capturing a proclivity to report. In this second case, the mechanism through which job jumping will be related to firm performance is less clear. It is possible that this second channel simply adds noise to the job jumping variable and if anything contributes measurement error that will make it harder to find significance on this variable.

3.2.2.3 Job turnover

My fourth workforce measure is job turnover, which is defined as the negative of current job tenure. Average job tenure for employees working at the banks in my sample is 4.7 years. There are a variety of reasons that may explain why banks have workforces who have spent less time working at that institution. It could be that the strategy of the bank requires more on extensive hiring of "foot soldiers" because bank-specific knowledge that employees acquire during longer job tenures is less relevant for business.[43] It could also be that banks tend to hire new employees from outside the firm

[43] Boot and Thakor (2000) think about a bank's business as a combination of relationship banking (based on long-term relationships with borrowers) and transaction banking involving arm's length transactions rather than relationships. Traditional banks are focused relatively more on the former type on lending and benefit from longer employee tenures.

rather than promoting from within. While we are not able to identify the exact reason banks' differ in the tenure of their employees, we can hypothesize (and do observe) a relationship between this measure and firm performance.

My focus on turnover is related to past literature on the role of experience and firm performance. Hermalin and Weisbach (1991) track the relationship between CEO tenure and profitability, finding that it does not affect profitability at low levels of tenure, but for those on the job for 15 years or more, each additional year tends to reduce profitability, likely because of agency or firm entrenchment. Berger, Kick, and Schaeck (2014) find that less experienced executive teams tend to be riskier and that board changes may increase portfolio risk. Chernenko, Hanson, and Sunderam (2015) find that experience predicted crisis performance, as inexperienced managers had almost twice the subprime exposure of their seasoned counterparts. Greenwood and Nagel (2009) rely on mutual fund manager data to conclude that young managers, but not old managers, exhibited trend chasing in their technology stock investments and were more heavily invested in tech stocks than their older colleagues. This is consistent with experimental literature (i.e. Smith et al. 1988 and Haruvy, Lahav, and Noussair 2007) who find that inexperienced subjects extrapolate recent price movements. While Chernenko, Hanson, and Sunderam (2015) and Greenwood and Nagel (2009) use age as a proxy for experience, in my analysis I rely on the bank-specific experience and focus on the question of whether the average worker tenure at a particular firm is related to how that firm will perform in crisis.

I also construct a cumulative measure, the W-index—the standardized sum of the four aforementioned variables, each of which is adjusted by bank size and standardized. Summary statistics on variables used in the analysis are presented in Table 3.1.

Table 3.1: Descriptive statistics

Variable	N	Mean	St. Dev.	25th Perc.	Median	75th Perc.
Performance						
Stock return (6/7–12/8)	222	-0.338	0.390	-0.654	-0.404	-0.027
Failed	224	0.219	0.414			
Fraction of loans charged-off in 2007-2009	223	0.011	0.010	0.003	0.008	0.015
Employee characteristics						
Fraction of MBA degree holders	224	0.163	0.077	0.103	0.168	0.211
Fraction of top school degree holders	224	0.102	0.086	0.044	0.079	0.128
Average job tenure	224	4.724	1.297	3.797	4.628	5.564
Fraction of job jumpers	224	0.428	0.087	0.372	0.429	0.484
Year-end 2006						
Book-to-market	224	0.537	0.257	0.421	0.489	0.615
Beta	224	1.006	0.095	0.944	1.016	1.079
Leverage	224	6.521	3.065	5.027	5.972	7.240
Assets ($B)	224	42.247	194.249	1.347	2.840	9.871
Net interest margin	224	0.041	0.012	0.034	0.039	0.047
2003-2006						
Highly rated securitization tranche holdings to total assets	224	0.013	0.037	0.000	0.002	0.016
Private MBS holdings to total assets	224	0.014	0.032	0.000	0.001	0.013
Interest income on loans to total loans	224	0.075	0.017	0.067	0.073	0.080
Volatility	224	0.016	0.004	0.013	0.016	0.019
Tail risk	224	0.035	0.009	0.028	0.035	0.040
Risk management index	85	0.629	0.297	0.380	0.557	0.871
Securitization activity indicator	224	0.192	0.395			
Securitization Ln($)	224	2.835	6.064	0.000	0.000	0.000
Housing bubble exposure	221	0.258	0.162	0.121	0.239	0.402
Assets growth	216	1.488	0.519	1.171	1.341	1.620
Number of employees growth	216	1.249	0.370	1.058	1.147	1.347
Assets per employee growth	216	1.204	0.263	1.052	1.167	1.284

Table 3.1: Descriptive statistics (Continued)

Variable	N	Mean	St. Dev.	25th Perc.	Median	75th Perc.
1998 Crisis						
1998 crisis return	179	-0.244	0.114	-0.293	-0.241	-0.184
Volatility 1H 1998	174	0.020	0.006	0.017	0.019	0.023
Volatility 2H 1998	179	0.030	0.010	0.024	0.028	0.036

Notes: This table reports summary statistics for my sample of bank holding companies (BHCs) in 2006. The sample consists of BHCs that have data available in CRSP and Call Reports and have employee resumes listed on a major professional networking website. *MBA* equals one if an employee has an MBA degree. *Top School* equals one if an employee has a degree from a top 50 university. *Job Jumper* equals one for employees that have switched more jobs than a median employee with similar career duration. *Job Tenure* measures employment duration at the current job; *Turnover* is defined as the negative of *Job Tenure*. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*).

3.3 Baseline

The baseline result relating workforce characteristics and different measures of bank performance in crisis is presented in different panels of Table 3.2. I start by examining stock returns in Panel A of Table 3.2. The dependent variable is measured as a buy-and-hold stock return between July 2007 and December 2008. A similar time period is used by Fahlenbrach and Stulz (2011) and Fahlenbrach et al. (2012). The reason why the return estimation period is capped at the end of 2008 is because "the losses in 2009 were at least partly affected by uncertainty about whether banks would be nationalized" (Fahlenbrach et al. 2012).[44] Over the course of my analysis, I control for standard variables used in the literature, including book-to-market value, beta, leverage, and total assets.[45] Year-end 2006 data is used for my bank control measures as

[44] I confirm that the results I document are qualitatively unchanged if stock returns are estimated between July 2007 and December 2009.

[45] I control for size conservatively using fixed effects for quintiles of assets. My results are robust to instead using as a control a continuous variable like log of assets or log of market value of equity.

well as for my workforce characteristics. Equity betas are estimated with daily returns data from January 2004 to December 2006 using a three-month T-bill rate as the risk-free rate and the value-weighted CRSP index as the market portfolio. Accordingly, there is no forward looking information on the right-hand side of the regressions, and thus they can be interpreted as predictive.

Table 3.2: Bank performance and workforce characteristics

Panel A: Stock returns

	(1)	(2)	(3)	(4)	(5)
MBA	-0.045*				
	[0.023]				
Top school		-0.094***			
		[0.022]			
Turnover			-0.135***		
			[0.021]		
Job jumper				-0.122***	
				[0.023]	
W-index					-0.145***
					[0.020]
Book-to-market	-0.321*	-0.316*	-0.228	-0.387**	-0.343*
	[0.186]	[0.172]	[0.178]	[0.172]	[0.175]
Beta	1.310***	1.444***	1.433***	1.161***	1.254***
	[0.413]	[0.386]	[0.392]	[0.420]	[0.385]
Leverage	0.012	0.006	0.006	0.012	0.012
	[0.017]	[0.016]	[0.016]	[0.017]	[0.016]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes
Observations	222	222	222	222	222
R-squared	0.170	0.215	0.275	0.252	0.296

Panel B: Bank failure (univariate)

	N	Mean	St. Dev.	25th. Perc.	Median	75th. Perc.
Failed	49	0.347	0.829	-0.112	0.373	0.748
Survived	175	-0.097	1.024	-0.781	-0.177	0.535
Failed–Survived		-0.444 ***				

Table 3.2: Bank performance and workforce characteristics (Continued)

Panel C: Bank failure (multivariate probit, marginal effects reported)

	(1)	(2)	(3)	(4)	(5)
MBA	0.046*				
	[0.028]				
Top school		0.005			
		[0.026]			
Turnover			0.066**		
			[0.028]		
Job jumper				0.095***	
				[0.028]	
W-index					0.077***
					[0.026]
Book-to-market	0.115	0.089	0.046	0.194	0.121
	[0.228]	[0.227]	[0.218]	[0.229]	[0.225]
Beta	-0.217	-0.303	-0.343	-0.12	-0.239
	[0.456]	[0.460]	[0.457]	[0.455]	[0.446]
Leverage	-0.019	-0.015	-0.013	-0.021	-0.017
	[0.018]	[0.018]	[0.017]	[0.018]	[0.018]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes
Observations	224	224	224	224	224

Panel D: Fraction of loans charged-off

	Total charge-offs	Charge-offs by category				
		Real estate	C&I	Consumer	Agriculture	Leases
	(1)	(2)	(3)	(4)	(5)	(6)
W-index	0.002***	0.002***	0.002**	0.001	0.007	0.169
	[0.001]	[0.001]	[0.001]	[0.002]	[0.007]	[0.157]
Net interest margin	0.297***	0.202**	0.089	0.12	0.073	-0.271
	[0.058]	[0.093]	[0.087]	[0.180]	[0.141]	[1.434]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	222	221	222	208	159	116
R-squared	0.149	0.065	0.026	0.14	0.01	0.003

Notes: This table reports results of cross-sectional OLS regressions relating bank performance to workforce characteristics. Panel A uses buy-and-hold stock returns from June 2007 to December 2008 as a measure of performance. Panel B and Panel C use bank failure, and Panel D used the fraction of loans charged-off in 2007–2009. Bank equity beta is measured during 2004–2006. Book-to-market, leverage, assets, and net interest margin are measured at the end of fiscal year 2006. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

In Columns 1–4, the explanatory variables of interest are 1) fraction of employees with an MBA; 2) fraction of employees with a top school degree; 3) job turnover; and 4) fraction of job jumpers. I document a negative and statistically significant relationship between bank performance and each of my workforce measures. In other words, a bank with a higher fraction of MBAs, a higher fraction of top school degree holders, more job jumpers and workers with shorter tenures in its workforce as of 2006 was more likely to do poorly during the 2007–2008 financial crisis. The results are economically significant as well. A one-standard deviation increase in the fraction of MBAs lowers crisis performance by 4.5 percentage points. Similarly, a one-standard deviation increase in the fraction of top school employees, job jumpers, and worker turnover lowers performance by 9.4, 13.5, and 12.2 percentage points respectively. Unsurprisingly, the results are similar if we report them for the aggregated W-index as in Column 5.

The coefficients on the other controls included in these baseline regressions have the expected sign, except for the coefficient beta. I get positive point estimates, meaning that banks with higher systematic risk did better in crisis. Fahlenbrach et al. (2012) find the same relationship between crisis returns and betas; they reconcile this with Acharya et al. (2010) who find the opposite relationship between the same variables, albeit in a sample of larger financial institutions.[46]

Not all banks survived the crisis period. The financial crisis was an epoch of disarray for the banking industry and it precipitated the failure of a large number of banks. The FDIC closed upwards of 500 banks in 2007–2014. In contrast, from 2000 to

[46] Banks in my sample are larger than banks in the sample of Fahlenbrach et al. (2012)—total assets as of year end 2006 of a median bank are about $2.8B and $2.0B, respectively. The reason my sample is shifted towards larger financial institutions is because employment data is more sparse for smaller banks.

2006, only 24 banks in the United States failed.[47] In my sample, 49/224 banks (roughly 20%) failed during the Great Recession. Thus, there is some concern that the results that I document for stock returns in Table 3.2 are driven by the fact that I am examining banks over different periods—as failed banks have returns for shorter horizons.[48] To account for this, I also consider differences in employee characteristics in banks that failed versus banks that survived. The results are reported in Panels B and C of Table 3.2 and are qualitatively the same as those for stock returns.

Particularly, I find that the W-index is substantially lower for an average bank that survived compared to an average bank that failed (Panel B of Table 3.2). In a multivariate setting in Panel C, I run a probit regression of bank failure on workforce measures and bank controls. Consistent with the stock performance results, each of the standalone workforce measures is negatively related to bank survival—and positively related to bank failure. The aggregate W-index is both statistically and economically significant and positively related to a bank's likelihood of failure. A one standard deviation increase in the W-index is associated with a 7.7 percentage point increase in the bank's probability of failure. Going forward, keeping statistical power and brevity considerations in mind, I report the results of the analysis using the W-index only. I have verified that the results hold for the standalone workforce variables as well.

During the financial crisis, banks were forced to recognize large losses through charging off their loans. These loans were written off because banks realized that they

[47] One can see the full list of bank failures on the FDIC website, by consulting https://www.fdic.gov/bank/individual/failed/banklist.html.

[48] Similar to Fahlenbrach et al. (2012), if a bank delists or fails before December 2008, I put proceeds in a cash account until December 2008.

had extended credit to individuals and institutions that would be unable to repay in the future. As an additional performance metric, I look to the fraction of loans charged-off in Panel D of Table 3.2. While stock returns serve as an overall indicator of bank performance, and bank failure is a categorical variable singling out those banks that fared the worst, charge-offs are a useful performance supplement as they provide unique information about the nature of loan origination in the pre-crisis period and the relationship between my workforce characteristics and strategy choices banks made about credit extension.

Panel D of Table 3.2 explores the relationship between the W-index and the fraction of loans charged off during the crisis period of 2007–2009. The results are consistent with those for stock returns and bank failures in Panel A, B, and C.[49]

In Columns 2–6, I report the same result for different categories of loans—real estate, commercial and industrial, consumer, agricultural, and leases. It is unsurprising that the baseline association I observe between total charge-offs and the W-index is driven by the categories of loans that exhibited the most expansion before the crisis: real estate, and commercial and industrial loans.

In Figure 3.1, I provide evidence consistent with the notion that the W-index is not a proxy for observable bank measures commonly studied. Particularly, I separate banks into quintiles based on: loans to assets, assets per employee, fraction of non-interest income in total income, core deposits to assets, tier-1 capital ratio, beta, book-to-market, share of real estate loans in total loans, share of commercial and industrial

[49] In the analysis of fraction of loans charged-off in financial crisis, I control for the net interest margin set equal to the fraction of net interest income in a year to total earning assets in a previous year.

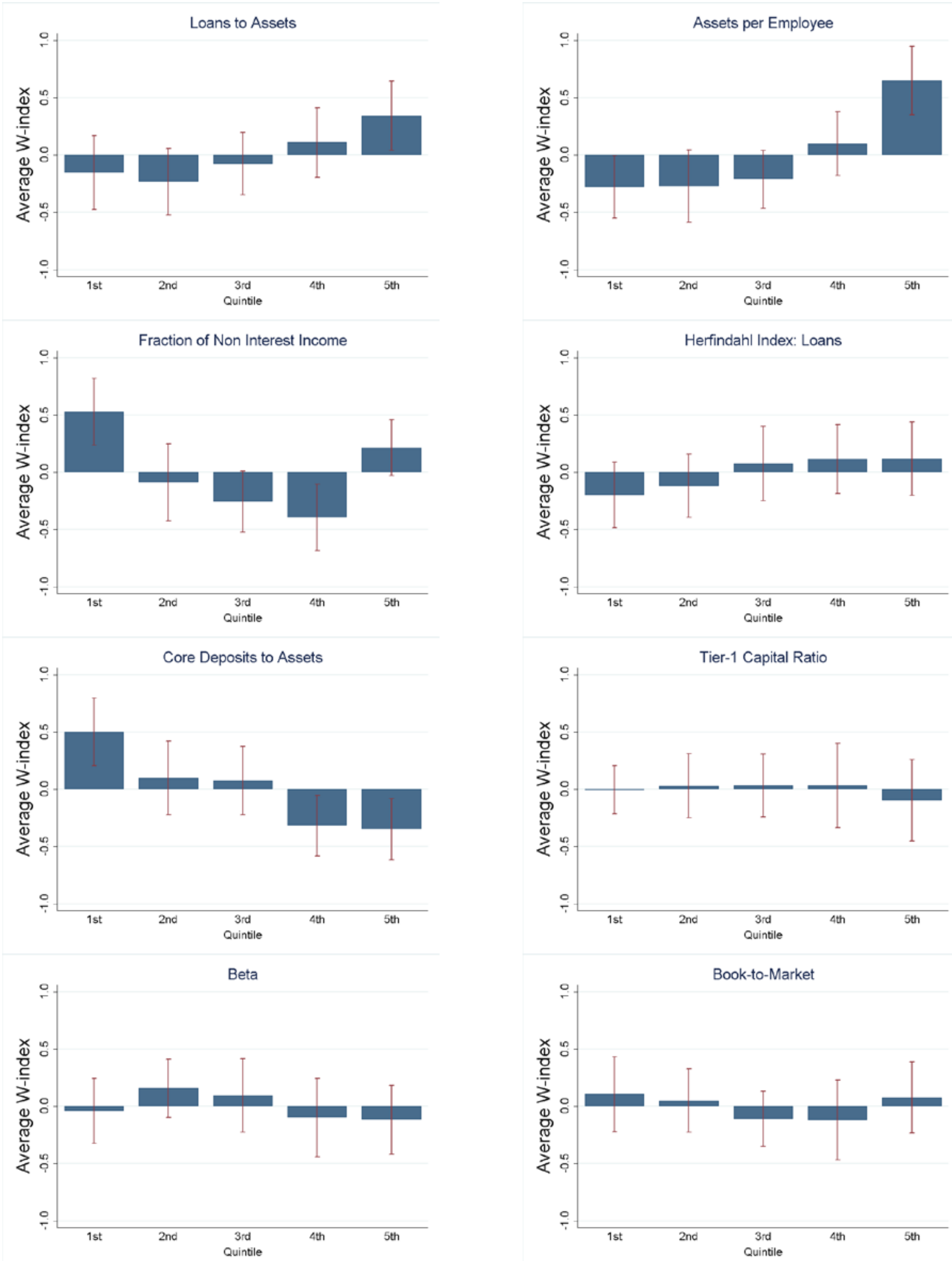

Figure 3.1: Distribution of W-index in banks with different characteristics

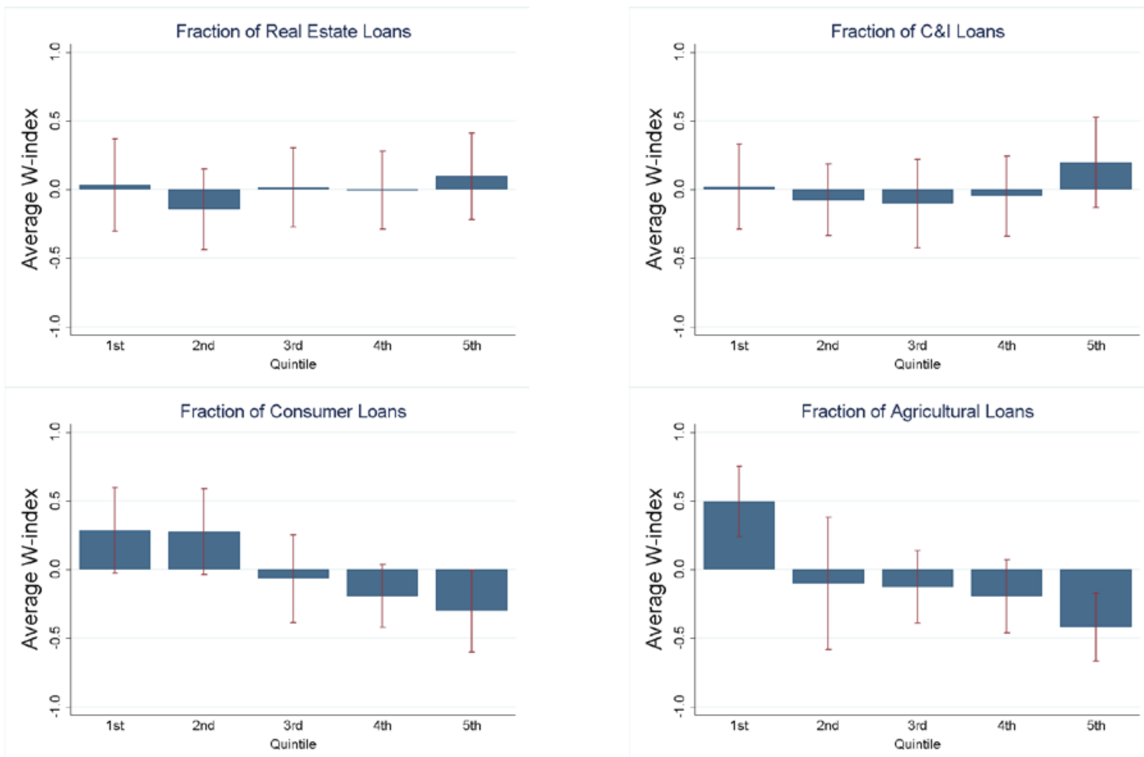

Figure 3.1: Distribution of W-index in banks with different characteristics (Continued)

Notes: This figure summarizes the relationships between the W-index and various observable bank characteristics. These characteristics are: 1) ratio of loans to assets; 2) assets per employee; 3) fraction of non-interest income; 4) Herfindahl loan index; 5) ratio of core deposits to assets; 6) tier-1 capital ratio; 7) beta; 8) book-to-market ratio; 9) fraction of real estate loans; 10) fraction of commercial and industrial loans; 11) fraction of consumer loans; 12) fraction of agricultural loans. Banks are sorted by quintile for each measure in the title of the individual charts below. The bars represent the average W-index of banks in that quintile; the 95% confidence interval is reported as well.

loans in total loans, share of consumer loans in total loans, share of agricultural loans in total loans, and the Herfindahl index for loan categories.[50] Figure 3.1 reports, by quintile, the average W-index for each of these measures as well as the 95% confidence interval. It does not appear that the W-index is strongly related to any of these observable measures in a way that can meaningfully explain the baseline results documented above. As such, the W-index can be thought of as an almost orthogonal measure to the more commonly used bank controls.

There are a few interesting relationships worth mentioning from Figure 3.1. First, we see that banks with high fractions of loans to assets tend to have high values on the W-index. Second, banks with high assets per employee also have high W-index values; these banks potentially pursue business models which endow employees with more impact. The fraction of non-interest income has an interesting U-shaped relationship with the W-index. Banks with higher fractions of consumer loans and, especially, agricultural loans tend to have lower W-index values. Finally, there is a negative relationship between the ratio of core deposits to assets and the W-index. This is consistent with the notion that banks engaging in less-risky activities (specifically, those with high proportions of agricultural loans and those with a higher fraction of assets financed by core deposits) have lower values of the W-index.

[50] The Herfindhal index is the sum of the squares of the shares in total loans of each category of loans—real estate loans, C&I loans, consumer loans, agricultural loans, and other loans.

Table 3.3: Horse race between the W-index and other bank measures

Additional control variable		W-index	N
Volatility of stock returns in 2003-2006	-6.267	-0.142***	222
	[9.507]	[0.021]	
Tier-1 capital ratio	0.236	-0.146***	221
	[0.439]	[0.020]	
Ratio of core deposits to assets	0.29	-0.133***	221
	[0.178]	[0.022]	
Housing bubble exposure	-0.386**	-0.129***	219
	[0.165]	[0.021]	
Securitization activity in 2003-2006	-0.04	-0.144***	222
	[0.060]	[0.021]	
Ratio of private MBS to assets	1.668***	-0.154***	221
	[0.433]	[0.020]	
Assets growth in 2003-2006	-0.157***	-0.112***	215
	[0.047]	[0.022]	
Assets per employee growth in 2003-2006	-0.237**	-0.136***	215
	[0.092]	[0.021]	
Number of employees growth in 2003-2006	-0.11	-0.128***	215
	[0.074]	[0.023]	
Ratio of loans to assets	-0.513***	-0.140***	221
	[0.176]	[0.020]	

Additional control variable		W-index	N
Fraction of non-interest income	0.523**	-0.146***	221
	[0.237]	[0.020]	
Ln(assets per employee)	-0.08	-0.136***	221
	[0.074]	[0.022]	
Residual compensation (A)	0.024	-0.174***	77
	[0.089]	[0.031]	
Residual compensation (B)	-0.081	-0.137***	221
	[0.090]	[0.024]	
Fraction of real estate loans	-0.400***	-0.149***	221
	[0.141]	[0.020]	
Fraction of C&I loans	0.167	-0.147***	221
	[0.194]	[0.021]	
Fraction of consumer loans	0.561*	-0.140***	221
	[0.287]	[0.020]	
Fraction of agricultural loans	-0.298	-0.146***	221
	[1.409]	[0.021]	
Fraction of other loans	0.353**	-0.150***	221
	[0.138]	[0.020]	
Herfindahl index of loan categories	-0.460**	-0.136***	221
	[0.181]	[0.020]	

Notes: This table reports results of cross-sectional OLS regressions relating bank performance to workforce characteristics. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The W-index is the standardized sum of four size-adjusted workforce characteristics (MBA, top school, turnover, and job jumper). Each line in this table replicates Model 5 in Table 3.2 (Panel A), but includes an additional control as specified in the line below. For brevity, only the point estimates and standard errors of the additional control and the W-index are reported. Bank equity beta is measured during 2004–2006. Book-to-market, leverage, assets, and other bank variables are measured at the end of fiscal year 2006. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

In Table 3.3, I run a sequence of horse races between the W-index and other potential predictors of bank's crisis performance. Specifically, I replicate Model 5 from Table 3.2 (Panel A) by adding additional control variables one at a time.[51] I find that in each of these additional regressions, adding controls has literally no impact on the W-index.[52]

Overall, it seems unlikely that the relationship between the W-index and bank performance is attributable to the W-index being a proxy for observable bank characteristics. The findings presented so far are consistent with the W-index being a novel measure related to bank performance in crisis.

The following section examines hypotheses to explain my baseline result.

3.4 Hypotheses development

I next develop and test hypotheses to explain my baseline result—that workforce characteristics of banks before the crisis are related to how well banks performed during the financial crisis and whether they survived at all.

In the three decades preceding the crisis, the financial sector experienced tremendous growth as measured in assets, employment, and wages (Greenwood and Scharfstein 2013; Philippon 2014). The growth was particularly strong from the early

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[51] I control sequentially for volatility of stock returns in 2003-2006; tier-1 capital ratio; the ratio of core deposits to assets; housing bubble exposure; securitization activity in 2003-2006; growth (in assets, assets/employee, and employees) from 2003-2006; ratio of loans to assets; fraction of non-interest income; log assets per employee; residual compensation; loan composition (fractions of real estate loans, commercial and industrial loans, consumer loans, agricultural loans, and the Herfindahl index of loan categories).

[52] Only 75 banks in my sample were successfully matched to the Execucomp dataset that Cheng, Hong, and Scheinkman (2015) use for executive compensation (A) in the construction of residual compensation. Hence, the number of observations in that horse race is low. I also construct an alternative measure of residual compensation (B) equal to the residual from the regression of total compensation per employee (defined for all banks, as this measure does not require Execucomp matching), and run a horse race between the W-index and this alternative.

2000s—following a short recession associated with the dot-com bubble bursting—until the financial crisis. It is possible that to accommodate this growth, banks recruited in this pre-Great Recession period a variety of employees with workforce characteristics different from those of the employees that had previously been hired.

Banks with the most aggressive pre-crisis growth were also those who performed the most poorly during the crisis. Thus, one possible explanation for the relationship between the W-index and bank performance during the crisis is that in the pre-crisis period, demand for bank employees outstripped supply. Banks who grew especially fast in the pre-crisis period to take advantage of the boom hired extensively, mechanically decreasing the average job tenure of their workforces. It is also possible that the people who they hired were more likely to be job jumpers (and thus unable or unwilling to retain stable employment). In the absence of candidates with relevant experience, banks could also have based their hiring decisions on (imperfect) signals of ability such as having an MBA degree or having a degree from a top school.

My first hypothesis focuses on the role that hiring during the pre-crisis expansion could play in explaining the baseline result.

> Hypothesis 1: W-index and pre-crisis hiring. The W-index is related to crisis performance because of the people hired during the pre-crisis expansion period by the most aggressively expanding—and most affected in crisis—banks.

My second hypothesis explores the possibility that the W-index is a proxy for a bank's quality. If this is the case, then some banks always perform poorly—in good and bad times—and some banks always perform well. The baseline effect could then be explained by the assignment of high W-index workforces to bad banks. A high W-index workforce could be viewed as subpar for the reasons mentioned in the discussion of the first hypothesis above.

> Hypothesis 2: W-index and persistent underperformance. The W-index is an indicator of underlying bank quality, sorting banks into persistent winners or losers in periods of crisis and no crisis alike.

My third hypothesis builds off the work of Beltratti and Stulz (2012) who show that banks that performed the worst in the financial crisis had above-average returns before the crisis began.[53] Their findings are consistent with the view that risk-taking before the crisis (through non-traditional banking) created short term gains for shareholders but left them "exposed to risks that manifested themselves during the crisis and had an adverse impact on banks" (Beltratti and Stulz 2012).

Accordingly, my third and final hypothesis investigates the relationship between the W-index and banks' risk-taking before the crisis. It is possible that high W-index banks took on more risk in the pre-crisis period, which led to adverse consequences in subsequent bad times. There are two channels through which high W-index workforces—with higher fractions of MBAs and top school degree-holders, workers with shorter tenures, and more job jumpers—could be

[53] Beltratti and Stulz (2012) seek to understand the significant variation in the cross-section of stock returns globally during the financial crisis. They document that the best-performing banks in crisis had significantly lower leverage at the end of 2006, had more traditional business models, and had higher deposits-to-assets ratios. They suggest that to the extent regulation served to augment crisis performance, it was because these regulations curbed newer or less traditional bank activities that turned out poorly during the crisis. Like Beltratti and Stulz (2012), I postulate and document a relationship between risky behavior and bank performance during the Great Recession.

associated with more aggressive banking in the pre-crisis period. On the one hand, people with these characteristics could have been matched to banks pursuing risky strategies to begin with. These banks needed employees with MBAs and top school graduates to execute complex transactions requiring a high level of financial expertise. And these banks were comfortable recruiting job jumpers—people without a track record of being loyal to their employers—since the nature of their business is distinct from traditional banking, which relies on bank-specific knowledge and benefits from long-term relationships with borrowers. For the same reason, these banks were comfortable sourcing talent externally as opposed to nurturing it internally and thus had higher turnover and lower average job tenures.

On the other hand, employees possessing these characteristics could also conceivably, within their discretion, have made decisions that on the margin resulted in higher risk-taking.[54]

> Hypothesis 3: W-index and pre-crisis risk-taking. The W-index is positively related to risk-taking by banks before the crisis, which increased their vulnerability to crisis.

3.5 Hypotheses evaluation

3.5.1 W-index and pre-crisis hiring

I start by laying the groundwork for testing my first hypothesis. First, it is true that the 2003–2006 period was accompanied by a substantial increase in the number of

[54] For example, these employees could conceivably originate subprime loans, purchase private mortgage-backed securities, or apply less scrutiny in the risk management process – taking on greater risk for their firm and reducing banks' stability in the lead-up to the crisis.

full-time equivalent employees in banks. An average bank in my sample experienced a 26% increase in the size of its workforce during the pre-crisis period. In Table 3.4, I show that the banks that grew the most rapidly also performed worst during the crisis. I capture the effect of bank growth using different variables (particularly: assets growth, employee growth overall, and assets/employee growth) and show that growth is in fact related to crisis underperformance. It is thus conceivable that *who* was hired during this pre-crisis period is related to crisis performance; that is, the workforce characteristics of recent hires could potentially explain the negative relationship between the W-index and crisis performance.

Table 3.4: Pre-crisis growth and crisis performance

	(1)	(2)	(3)	(4)
Assets growth	-0.250***			
	[0.045]			
Number of employees growth		-0.261***		-0.304***
		[0.070]		[0.065]
Assets per employee growth			-0.314***	-0.380***
			[0.092]	[0.089]
Book-to-market	-0.195	-0.245	-0.3	-0.185
	[0.197]	[0.204]	[0.192]	[0.199]
Beta	1.160***	1.279***	1.326***	1.146***
	[0.412]	[0.427]	[0.414]	[0.404]
Leverage	-0.003	0	0.013	0.001
	[0.018]	[0.019]	[0.018]	[0.018]
Assets quintile FEs	Yes	Yes	Yes	Yes
Observations	215	215	215	215
R-squared	0.256	0.209	0.194	0.270

Notes: This table relates crisis performance of banks to their growth in the pre-crisis period. Bank performance is measured by stock returns from June 2007 to December 2008. Models 1-3 use standalone measures of growth for (1) assets growth; (2) employees growth; and (3) assets per employee growth. These variables are computed for the pre-crisis period. Bank equity beta is measured during 2004–2006. Book-to-market, leverage, and assets are measured at the end of fiscal year 2006. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Table 3.5: Persistence

	(1) 2005	(2) 2004	(3) 2003	(4) 2002	(5) 2001	(6) 2000
W-index	-0.089***	-0.094***	-0.091***	-0.082***	-0.053*	-0.072**
	[0.024]	[0.025]	[0.026]	[0.028]	[0.029]	[0.029]
Assets growth	-0.215***	-0.225***	-0.215***	-0.255***	-0.261***	-0.274***
	[0.047]	[0.057]	[0.061]	[0.065]	[0.065]	[0.065]
Book-to-market	-0.326	-0.303	-0.379*	-0.312	-0.334	-0.424*
	[0.211]	[0.197]	[0.199]	[0.210]	[0.241]	[0.242]
Beta	1.307***	0.977**	0.807**	1.251**	1.187***	1.375***
	[0.400]	[0.408]	[0.403]	[0.483]	[0.441]	[0.403]
Leverage	0.013	0.008	0.011	-0.003	-0.011	-0.019
	[0.019]	[0.018]	[0.019]	[0.018]	[0.020]	[0.019]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	206	189	175	159	146	135
R-squared	0.313	0.342	0.357	0.371	0.365	0.383

Notes: This table reports results of cross-sectional OLS regressions relating bank performance to workforce characteristics. Bank performance is measured by stock returns from June 2007 to December 2008. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). Models 1–6 measure the W-index in different years—from 2005 to 2000—as indicated in the header of the table. Book-to-market, leverage, and assets are measured at the end of fiscal year 2006. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Table 3.5 presents direct evidence against this hypothesis. I establish a persistent relationship between performance and the W-index, controlling for assets growth in the pre-crisis period. Importantly, instead of focusing on those employees who worked at the firm in 2006, I compute the W-index for the workforce in earlier years. In particular, I go back one year at a time all the way back to 2000 and sequentially recalculate the W-index for the bank's workforce at the end of each year. Even though many of the individuals comprising the workforce in the earlier years leave the firm long before the onset of the crisis, the W-indices as of every year from 2000 to 2005 remain significant predictors of bank underperformance in crisis. This is noteworthy given that there are over 6 years between the time when the workforce measure is estimated at the end of 2000 (Model 6) and July 2007 when I start computing buy-and-hold returns to assess crisis performance.[55] This finding rejects the hypothesis that the relationship between the W-index and performance is somehow driven by hiring practices in the lead-up to the crisis. On the contrary, the workforce composition of banks beginning in 2000, several years before the crisis, is a significant predictor of crisis performance. This result argues against the first hypothesis and drives me to consider additional explanations for the documented relationship between workforce characteristics and bank performance.

3.5.2 W-index and persistent underperformance.

As demonstrated in Table 3.5, the W-index remains predictive of crisis performance even when rolled back several years. In other words, the characteristics of banks' workforces as far back as 2000 are statistically and economically significant in predicting performance during the crisis. A new hypothesis to explain the baseline effect emerges from this set of results. It is possible that the W-index is in fact an indicator of bank quality—some banks always perform poorly, and others always perform well. I next test this hypothesis by looking at how the W-index relates to bank performance in the pre-crisis period.

If the W-index is indeed a proxy for a bank's underlying quality, then there should be a negative relationship between the W-index and bank performance not only

[55] As I demonstrate later in the paper (Table 3.12), even the W-index calculated as far back as 1997 is significant in predicting firm performance during the Great Recession. So, I am able to roll back these workforce measures at least a decade and still observe them having a strong and significant relationship with crisis performance.

in bad times, but in good times as well. In particular, high W-index banks should have lower stock returns in the pre-crisis period also. This is not what I observe.

Table 3.6: Pre-crisis dynamics

	Stock return in 2003–2006	Compensation per employee in 2003–2006	Assets per employee growth in 2003–2006
	(1)	(2)	(3)
W-index	0.119**	11.076***	0.046*
	[0.054]	[1.872]	[0.026]
Book-to-market	0.218	6.457	0.215
	[0.476]	[11.496]	[0.268]
Beta	0.38	27.876*	-0.393***
	[0.355]	[15.760]	[0.138]
Leverage	0.038	0.015	-0.016
	[0.036]	[0.959]	[0.022]
Assets quintile FEs	Yes	Yes	Yes
Observations	154	154	152
R-squared	0.192	0.457	0.063

Notes: This table reports results of cross-sectional OLS regressions relating bank performance, compensation per employee, and assets per employee growth to workforce characteristics. Bank performance in Model 1 is measured as buy-and-hold stock returns from January 2003 to December 2006. The dependent variable in Model 2 is the average ratio of total salaries and employee benefits to the total number of employees from 2003 to 2006. The dependent variable in Model 3 is the growth in the ratio of total assets per employee from 2003 to 2006. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). Bank equity beta is measured during 2000–2002. Book-to-market, leverage, assets, and workforce characteristics are measured at the end of fiscal year 2002. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Column 1 of Table 3.6 illustrates that the W-index is positively related to bank performance in the pre-crisis period. The explanatory variable is buy-and-hold returns from January 2003 to December 2006. To ensure that my regressions have a predictive interpretation, I use the W-index as of 2002—and not the 2006 measure that I use in the baseline analysis.[56] I find that banks with high W-indexes did *better* in the lead-up

[56] It has been established in Table 3.5 that the 2002 W-index is also predictive of crisis performance.

to the crisis. This result is consistent with Beltratti and Stulz (2012) who show that the best pre-crisis performers became the worst performers in crisis. In Column 2, I show that these same high-W banks had significantly higher compensation per employee and assets per employee growth (Column 3) in the lead-up to the crisis.

My findings provide evidence against the hypothesis that the W-index is picking up latent underlying quality features of banks that sort them into persistent winners or losers. In fact, high W-index banks performed well before the crisis but fared poorly in the crisis itself. The fact that those banks that performed well for their stockholders in the pre-crisis period also paid their employees more and exhibited higher assets per employee growth suggests that there may be fundamental differences in the business models of these banks as compared to their low W-index counterparts.[57]

3.5.3 W-index and pre-crisis risk-taking

Having established that high W-index banks fared well in the pre-crisis period, but collapsed during the crisis, I proceed to my next hypothesis—that perhaps the W-index is capturing risk-taking in the pre-crisis period of boom. I build up support for this hypothesis by connecting my W-index with a variety of measures of bank risk-taking, risk realization, and risk management.

Table 3.7 reports the relationship between the W-index and a variety of risk measures. Column 1 considers the fraction of assets held in highly rated tranches of securitization (following Erel, Nadauld, and Stulz 2014).[58] This measure captures the

[57] Brickley et al. (2012) show that bankers' banks, for example, have higher assets per employee than a typical bank precisely because of the nature of their business—they supply no retail banking services.

[58] Erel, Nadauld, and Stulz (2014) define the highly rated residual as the value of securities assigned an AA or AAA risk weight that are not government or agency-affiliated (i.e., subprime residual mortgages and collateralized debt obligations).

proportion of a bank's assets that were devoted to those synthetic securities that were deemed to not carry much risk in the lead-up to the crisis but ended up losing a significant amount of value during the crisis. Erel, Nadauld, and Stulz (2014) find that banks with higher holdings of highly rated residuals performed worse in the crisis. As expected, we find a statistically and economically significant relationship between the W-index and the ratio of highly rated residual to assets.

Table 3.7: Pre-crisis risk-taking

	Highly rated residual	Private MBS	Interest on loans	Volatility	Tail risk	Risk management index
	(1)	(2)	(3)	(4)	(5)	(6)
W-index	0.008***	0.005**	0.003***	0.001**	0.001**	-0.087**
	[0.003]	[0.003]	[0.001]	[0.000]	[0.001]	[0.037]
Book-to-market	-0.044	-0.039	0.009	0.001	0.002	0.120
	[0.031]	[0.026]	[0.016]	[0.002]	[0.005]	[0.258]
Beta	0.032	0.016	-0.003	0.002	0.000	0.359
	[0.021]	[0.017]	[0.009]	[0.002]	[0.005]	[0.396]
Leverage	0.003	0.002	-0.001	0.000	0.000	-0.019
	[0.002]	[0.002]	[0.001]	[0.000]	[0.000]	[0.022]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	154	154	175	154	154	74
R-squared	0.244	0.185	0.117	0.432	0.368	0.290

Notes: This table reports results of cross-sectional OLS regressions relating pre-crisis risk-taking to workforce characteristics. Model 1 uses the fraction of assets held in highly rated tranches of securitization, on average, between 2003 and 2006. Model 2 uses the fraction of assets held in private MBS, on average, between 2003 and 2006. The dependent variable in Model 3 is the ratio of interest income on loans to total loans as of the previous year, on average, between 2003 and 2006. Volatility of daily stock returns from January 2003 to December 2006 is used as a dependent variable in Model 4. Tail risk in Model 5 is calculated as the negative of the stock's average return over its 5% worst trading days. The Risk Management Index in Model 6 measures the strength of bank risk management. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). Bank equity beta is measured during 2000–2002. Book-to-market, leverage, and assets are measured at the end of fiscal year 2002. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

In Column 2, I use as a measure of risk the fraction of private mortgage-backed securities to assets. Consistent with the risk-taking hypothesis, I find that having a higher proportion of private MBS to assets is associated with a higher W-index. Column 3 shows that having higher interest on loans—in other words, having an ex-ante riskier loan portfolio—is also related to higher W-indices.

Researchers can infer ex-ante risk-taking from the realized volatility of stock returns. I do this in Column 4 of Table 3.7. It turns out that higher values of the W-index are, in fact, related to higher realized stock return volatility in 2003–2006. This is consistent with the proposition that high-W index banks engaged in more risk-taking before the crisis.[59]

In Column 5, I also use a measure of risk based on the expected shortfall measure, capturing expected loss conditional on returns falling below some percentile-based threshold (see, e.g., Acharya et al. 2010). Following Ellul and Yerramilli (2013), I refer to this measure as *Tail Risk* and use the 5% worst return days for each stock in my calculation. In particular, *Tail Risk* is set equal to the negative of the stock's average return over its 5% worst trading days.[60] Column 5 of Table 3.7 shows that tail risk realized before the crisis is in fact positively related to the W-index of banks as of

[59] Highly rated securitization tranches were naturally perceived as safe in the pre-crisis period and did not add volatility to banks' stock returns. High W-index banks had higher volatility before the crisis because they presumably took on more risk through other channels. As such, this result is a testament to the multi-dimensional nature of banks' risk taking, discussed previously in this paper.

[60] Ellul and Yerramilli (2013) explore the effect of risk management functions on tail risk. They view tail risk as the extent to which banks "enhance performance in the short run" before risk "materializes [and causes] significant damage to the institution." Put differently, banks with high (low) tail risk are likely pursuing aggressive (conservative) business models. In this paper, I think about tail risk in a similar fashion.

the year-end 2002. Note, however, that neither my volatility nor my tail risk results demonstrate how exactly the risk was taken.

In Column 6, I use the risk management index (RMI) of Ellul and Yerramilli (2013). RMI measures the strength of risk management at bank holding companies. To construct a measure of a bank's ability to mitigate large losses, Ellul and Yerramilli (2013) rely on information on the organizational structure of banks from their 10-K statements, proxy statements, and annual reports. I find that there is a strong negative relationship between risk management and the W-index at the BHCs in my sample. This suggests that banks with the weakest risk management practices also had high values of the W-index.[61]

I have shown my workforce characteristics are negatively related to banks' performance in the financial crisis and positively related to their performance before the crisis. High W-index banks had a higher fraction of assets held in highly rated securitization tranches, a higher fraction of private MBS to assets, and also had riskier loans. They also experienced more volatility, had higher tail risk, and had less stringent risk management. These findings are consistent with the notion that high-W index banks engaged in more risk-taking before the crisis that possibly led to better performance during the boom and increased their vulnerability to the bust.

In the subsequent section I explore whether the *form* of risk-taking was different in high-W index banks depending on the growth of house prices—central to the financial crisis—in areas where they were located.

[61] This result does not imply in any way that RMI determines the W-index or the other way round. It is in fact plausible that both are related to an unobserved variable associated with banks' risk appetite.

3.6 Exposure to the housing bubble

Given the pivotal role that the mid-2000s real estate boom played in the financial crisis, it is natural to add it into consideration when thinking about the relationship between banks' performance in crisis and workforce characteristics. To do so, I need a measure of banks' exposure to the housing bubble. My measure is constructed from two datasets. State-level growth in median home prices from 2003 to 2006 is obtained from Zillow. From the 2006 Summary of Deposits, I get the by-state distribution of banks' deposits. I then construct each bank's exposure to the housing bubble as a deposit-weighted average of home price growth rates in the states where a bank has branches.[62] To give a specific example, banks with branches located in states like Nevada—with booming house prices in the lead-up to the crisis—score high on the housing bubble exposure measure, whereas banks located in states like Iowa—with sluggish home price growth—score low. I next explore how crisis performance and the form of pre-crisis risk-taking in high W-index banks is related to the growth of home prices in banks' locations.

First, I confirm in Table 3.8 that high W-index banks performed worse in the recent financial crisis—in terms of buy-and-hold stock returns—irrespectively of whether they were located in areas with booming or sluggish house prices. Columns 1–3 report the analysis for the full sample and control for housing bubble exposure in different ways. I use the continuous variable of bubble exposure in Column 1 and fixed effects for quintiles and deciles of that continuous measure in Columns 2 and 3, respectively.

[62] The results are robust to instead restricting the sample of banks for this analysis to those whose deposits are located in only one state.

Table 3.8: Housing bubble

(Sub)sample:	Full	Full	Full	Low bubble location	High bubble location
	(1)	(2)	(3)	(4)	(5)
W-index	-0.129***	-0.127***	-0.120***	-0.153***	-0.111***
	[0.021]	[0.022]	[0.022]	[0.038]	[0.024]
Housing bubble	-0.386**			-0.416	-0.846***
	[0.165]			[0.646]	[0.293]
Book-to-market	-0.344*	-0.371**	-0.322*	0.024	-0.612**
	[0.176]	[0.175]	[0.182]	[0.223]	[0.280]
Beta	1.156***	1.159***	1.131***	0.41	1.818***
	[0.412]	[0.413]	[0.432]	[0.547]	[0.522]
Leverage	0.011	0.013	0.011	-0.029	0.046**
	[0.017]	[0.017]	[0.018]	[0.020]	[0.022]
Fixed Effects					
Housing bubble					
Quintile	No	Yes	No	No	No
Decile	No	No	Yes	No	No
Assets quintile	Yes	Yes	Yes	Yes	Yes
Observations	219	219	219	109	110
R-squared	0.317	0.334	0.372	0.315	0.4

Notes: This table reports results of cross-sectional OLS regressions relating bank performance to workforce characteristics. Bank performance is measured as buy-and-hold stock returns from June 2007 to December 2008. *Housing Bubble* is the growth of home prices in a bank's locations. It is measured as a deposit-weighted average of the increase in 2003–2006 of median home prices in states where a bank had branches in 2006. Models 1–3 report the results for the full sample. Models 4–5 report the results separately for banks located in areas with low (below median) and with high (above median) home price growth, respectively. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). Bank equity beta is measured during 2004–2006. Book-to-market, leverage, and assets are measured at the end of fiscal year 2006. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Columns 4–5 report the results separately for banks located in areas with low (below median) and with high (above median) home price growth. In each of the specifications, my baseline result remains intact, and the W-index is still a significant negative predictor of bank performance during crisis. Econometrically, this suggests that my results are not driven by differences in the W-index in areas with high exposure to the real estate bubble relative to areas with low exposure to the bubble. Particularly, the W-index turns out to be an important predictor of crisis performance for banks *within* the same level of housing bubble exposure. In other words, high W-index banks in states like Nevada fare worse in crisis compared to low-W index banks in states like Nevada; and the same is true for banks located in states like Iowa. Taken together with the earlier results, it is plausible that high W-index banks took more risk in the pre-crisis years—irrespectively of whether they were located in areas with booming or sluggish house prices—and were more vulnerable to the crisis for that reason. I next explore whether the *form* of pre-crisis risk-taking varies depending on the dynamics of home prices.

Panels A and B of Table 3.9 examine two different forms of housing-related risk-taking—securitization activity and holding of real estate derivatives, respectively. For securitization, I calculate the average outstanding principle balance of assets sold and securitized with servicing retained or with recourse or other seller-provided credit enhancements between 2003 and 2006. I use both the continuous variable and an indicator variable for it being greater than zero (evidence of some securitization activity) as dependent variables in Panel A.[63] I also use as an ex-ante measure of loans'

[63] I follow Erel, Nadauld, and Stulz (2014) in defining variables to capture banks' securitization activities.

Table 3.9: Housing bubble and risk-taking

Panel A: Risky loans and securitization

Subsample:	Low housing bubble location			High housing bubble location		
	Interest on loans	Securitization in 2003–2006		Interest on loans	Securitization in 2003–2006	
		> 0	Ln(\$)		> 0	Ln(\$)
	(1)	(2)	(3)	(4)	(5)	(6)
W-index	0.001	-0.013	-0.016	0.003**	0.056**	0.690**
	[0.002]	[0.043]	[0.636]	[0.001]	[0.026]	[0.313]
Share of real estate loans	0.024	-0.455*	-7.396*	0.016	-0.584**	-9.862*
	[0.022]	[0.265]	[4.118]	[0.023]	[0.281]	[5.076]
Share of C&I Loans	-0.005	-0.486	-8.192	-0.001	-0.697*	-12.021*
	[0.020]	[0.424]	[5.861]	[0.025]	[0.358]	[6.101]
Net interest margin	0.145	-1.607	-39.063	0.533***	-1.788	-24.405
	[0.547]	[4.760]	[77.465]	[0.120]	[1.424]	[25.713]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110	110	110	110	110	110
R-squared	0.16	0.32	0.358	0.389	0.461	0.519

Panel B: Holdings of risky assets and risk management

	Highly rated residual		Private MBS		Risk management index	
Housing bubble subsample:	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
W-index	0.016**	0.003*	0.011*	0.002	-0.085*	-0.026
	[0.007]	[0.002]	[0.006]	[0.001]	[0.049]	[0.028]
Book-to-market	0.013	-0.047	0.047	-0.044	-0.100	-0.168
	[0.031]	[0.030]	[0.037]	[0.030]	[0.337]	[0.317]
Beta	-0.02	-0.019	-0.002	0.002	-0.662	-2.785***
	[0.041]	[0.029]	[0.032]	[0.029]	[0.918]	[1.000]
Leverage	-0.002	0.002	-0.005	0.002	0.005	0.02
	[0.003]	[0.002]	[0.003]	[0.002]	[0.029]	[0.028]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110	111	110	111	42	41
R-squared	0.223	0.251	0.202	0.206	0.299	0.44

Table 3.9: Housing bubble and risk-taking (Continued)

Panel C: Fraction of loans charged-off in crisis

(Sub)sample:	Full	Full	Full	Low bubble location	High bubble location
	(1)	(2)	(3)	(4)	(5)
W-index	0.002***	0.002**	0.002**	0.004***	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Housing bubble	0.007			0.002	0.029***
	[0.005]			[0.014]	[0.008]
Net interest margin	0.263***	0.249***	0.252***	0.395***	0.245***
	[0.063]	[0.063]	[0.065]	[0.110]	[0.081]
Fixed Effects					
Housing bubble					
Quintile	No	Yes	No	No	No
Decile	No	No	Yes	No	No
Assets quintile	Yes	Yes	Yes	Yes	Yes
Observations	220	220	220	110	110
R-squared	0.191	0.204	0.260	0.204	0.305

Notes: This table reports results of cross-sectional OLS regressions relating bank risk-taking before the financial crisis to workforce characteristics. *Highly Rated Residual* is the fraction of assets held in highly rated tranches of securitization, on average, between 2003 and 2006. *Private MBS* is the fraction of assets held in private MBS, on average, between 2003 and 2006. The *Risk Management Index* measures the strength of bank risk management. *Interest on Loans* is the ratio of interest income on loans to total loans as of the previous year, on average, between 2003 and 2006. The dollar amount of *securitization* is set equal to the average outstanding principle balance of assets sold and securitized with servicing retained or with recourse or other seller-provided credit enhancements between 2003 and 2006. *Housing Bubble* is the growth of home prices in a bank's locations. It is measured as a weighted average of the increase in 2003–2006 of median home prices in states where a bank had branches in 2006. This measure is weighted by the amount of a bank's deposits in each of these states. Results are reported separately for banks located in areas with low (below median) and with high (above median) house prices growth, as indicated in the header of each column. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). Bank equity beta is measured during 2000–2002. Book-to-market, leverage, assets, share of real estate loans in total loans, share of C&I loans in total loans, and net interest margin are measured at the end of fiscal year 2002. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

riskiness the interest on loans, introduced in Table 3.7. For the real estate derivatives, I use the same measures I introduced in Table 3.7—fractions of assets held in highly rated tranches of securitization and fraction of assets held in private mortgage-backed securities.

It turns out that there is a separating equilibrium in the *form* of banks' risk-taking that depends on the dynamics of home prices in banks' locations. High W-index banks based in states like Iowa—with low bubble exposure—do not have as much of an opportunity to extend and securitize risky loans secured by real estate. They can and do, however, choose to be exposed to the housing bubble by holding synthetic assets backed by real estate on their balance sheets.[64] On the contrary, high W-index banks based in states like Nevada are active in originating risky loans (with high interest rates) and securitizing them, but not in holding real estate derivatives on their books. Panel A of Table 3.9 shows that the relationship between interest on loans and securitization activity in 2003–2006 is related to the W-index only in the subsample of banks with *above*-median exposure to the housing bubble. Panel B of Table 3.9 illustrates that the relationship between holdings of real estate-linked securities is stronger for banks with *below*-median exposure the housing bubble. Interestingly, the quality of bank's risk management is negatively correlated with the W-index for banks in areas with sluggish growth of house prices. In other words, high W-index banks in states like Iowa had poor risk management practices. This may help explain why these banks had higher holdings of securities deemed toxic as the crisis unraveled.[65]

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[64] Particularly, they hold highly rated securitization tranches and private mortgage-backed securities.

[65] This result should be taken with caution because RMI—the risk management index—is defined for less than half of the banks in my sample.

This set of results warrants an interesting interpretation. What I observe could be a consequence of risk transfer between banks. High W-index banks in states with booming real estate prices originated high-yield loans, securitized them, and sold real estate-linked derivatives to high W-index banks located in states with sluggish growth in home prices. It is precisely the opportunity to securitize risky loans that made this risk transfer possible and enabled high W-index banks in states like Iowa—to their detriment—to gain exposure to the housing bubble through holdings of private MBS and highly-rated securitization tranches. To a certain extent, this risk transfer mitigated the losses that high W-index banks in states like Nevada experienced in crisis, because some of the loans that they would have charged-off in crisis were already off their balance sheets through securitization. This is confirmed in Panel C of Table 3.9 which shows that the relationship between the fraction of loans charged-off in crisis and the W-index is weaker for banks located in areas with high home price growth pre-crisis.

3.7 Local Labor Markets and the W-Index

It is possible that the relationship between the W-index and bank performance reflects local labor market conditions. For example, it may be the case that MBA or top school degree holders are concentrated—and thus available for employment—in only certain areas. Banks sourcing their labor force from these locations will hire from a pool of employees stacked in favor MBAs and top school graduates. In case employees with such characteristics are mostly available in regions with a highly pronounced boom-bust cycle, the relationship I document may just reflect local hiring. I rule out this possibility in Table 3.10.

Table 3.10: Location- and bank-specific effects

	Highly rated residual (1)	Private MBS (2)	Interest on loans (3)	Volatility (4)	Tail risk (5)	Crisis stock returns (6)	% of charge-Offs in crisis (7)
Local W-index	0.007	0.003	0.002	0.001**	0.001**	-0.071***	0.001
	[0.004]	[0.003]	[0.001]	[0.000]	[0.001]	[0.027]	[0.001]
Bank W-index	0.006**	0.005**	0.003***	0.000*	0.001*	-0.122***	0.002*
	[0.003]	[0.002]	[0.001]	[0.000]	[0.000]	[0.031]	[0.001]
Book-to-market	-0.045	-0.042	0.01	0.002	0.004	-0.05	
	[0.030]	[0.027]	[0.016]	[0.002]	[0.004]	[0.250]	
Beta	0.032	0.015	-0.003	0.002	0.000	0.382**	
	[0.021]	[0.018]	[0.009]	[0.002]	[0.005]	[0.168]	
Leverage	0.003	0.002	-0.002	0.000	0.000	0.002	
	[0.002]	[0.002]	[0.001]	[0.000]	[0.000]	[0.019]	
Net interest margin							0.280***
							[0.095]
Assets quintile FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149	149	169	149	149	148	148
R-squared	0.251	0.193	0.115	0.426	0.36	0.241	0.111

Notes: This table reports results of cross-sectional OLS regressions relating banks' pre-crisis risk-taking (Model 1–5) and crisis performance (Models 6–7) to workforce characteristics. *Highly Rated Residual* is the fraction of assets held in highly rated tranches of securitization, on average, between 2003 and 2006. *Private MBS* is the fraction of assets held in private MBS, on average, between 2003 and 2006. *Interest on Loans* is the ratio of interest income on loans to total loans as of the previous year, on average, between 2003 and 2006. *Volatility* of daily stock returns is measured between 2003 and 2006. *Tail Risk* is the negative of the average return on the 5% of the worst trading days of a stock in 2003–2006. Bank performance is measured as buy-and-hold stock returns from June 2007 to December 2008 and fraction of loans charged-off in 2007–2009. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). *Local W-index* is set equal to the average *W-index* of other banks located in the same state as the bank under consideration. *Bank W-index* is the difference between *W-index* and *Local W-index*. Bank equity beta is measured during 2000–2002. Book-to-market, leverage, assets, and net interest margin are measured at the end of fiscal year 2002. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

I start by constructing, for each bank, an average W-index of *other* banks located in the same state with the bank under consideration. I call this the *Local W-index*.[66] I also introduce a *Bank W-index* which I obtain by subtracting *Local W-index* from the basic *W-index* measure. Put differently, I decompose the W-index of each bank into its local component and into its bank-specific component. I then use both the location and bank-specific W-indices in a series of regressions to understand banks' pre-crisis risk taking (Columns 1–5) and bank performance (Columns 6–7). I find that for ex-ante risk-taking measures (holdings of highly rated securitization tranches, private MBS, and riskiness of loans in Columns 1–3), it is only the bank-specific W-index that is relevant. For ex-post market-based realized risk measures (i.e., volatility in Column 4 and tail risk in Column 5) it appears that both the Local and Bank W-indices matter. The same is true for stock performance in crisis (Column 6), though for loan charge-offs only a bank's own workforce characteristics are important.

Taken together, these results suggest that while the workforce characteristics of the locality may be informative on bank volatility, the balance sheet ex-ante measures of risk-taking are entirely driven by banks' own workforce characteristics and not by those of the locality as a whole. These results are consistent with the fact that workforce characteristics are not simply picking up the location effects but rather are reflective of a bank's strategy or its predisposition to take on risk.

3.8 Job Relevance and the W-Index

To utilize the full power of my individual-level dataset, I can use job titles and job descriptions to classify people into different groups depending on their function in a

[66] My Local W-index measure is—by its nature—defined only for banks in states that have more than one bank in my sample.

bank. If, as I hypothesize above, the relationship between the W-index and bank performance stems from bank risk-taking, then I expect that this relationship will be more pronounced if the analysis is performed on those employees who work in areas of the bank where they have impact on risk-taking (e.g., loan origination) rather than less relevant occupations (e.g., support roles).

Table 3.11 provides a brief snapshot of the job descriptions I observe in my dataset. I start by stemming words in each job description. Then I discard the words from the list of common stop words (such as "and", "the", "a", etc.). Panel A reports the 50 stemmed words most frequently used in job descriptions of bank employees in my sample. The list contains stems that are related to banking in general (e.g., *manag*, *busi*, *bank*, etc.) as well as words that provide information about an employee's job function (e.g., *loan*, *sale*, *risk*, etc.).

I then use a latent Dirichlet allocation (LDA)[67] model of topic discovery to see if individual job descriptions group together in a meaningful way. LDA is a machine learning method that examines the relative frequencies of words in different documents and posits that each document is a combination of a small number of *topics*—collections of words—from which the words used in the document are drawn.[68] The top 5 words for each topic identified by an LDA model with 9 topics are reported in Panel B of Table 3.11. These are the words most representative of a specific topic. The topics are reported by the algorithm in no particular order. In this particular case, I have sorted

[67] LDA is a popular model for collections of discrete data, such as texts, introduced by Blei et al. (2003).

[68] In terms of applications of topic models, Blei and Lafferty (2006) use dynamic topic models to analyze archives of the journal *Science* from 1880 through 2000 and can infer the rise and fall of a specific topic's (e.g., atomic physics) popularity over time. More recently, Jelveh et al. (2015) extend methods introduced by Gentzkow and Shapiro (2010) and apply LDA to economists' academic papers to identify their political ideology and eventually its impact on research results.

them in a way that allows for intuitive interpretation of the first four topics. Topic 1, for example, features the keywords *loan*, *mortgag*, *account*, *process*, and *review* and is likely describing employees whose job functions are related to loans. Topic 2—with the keywords *risk*, *finance*, *invest*, *manag*, *bank*—potentially identifies risk management-related roles. Topic 3 has the keywords *custom*, *manag*, *sale*, *service*, *busi* and is thus likely associated with customer- or sales-related job functions. Finally, Topic 4 contains the keywords *system*, *applic*, *support*, *data*, *test* and plausibly points to employees that work in IT roles. The remaining topics are hard to interpret.

The LDA results reported in Panel B of Table 3.11—and particularly the possibility of identifying reasonable topics—speaks to the meaningfulness of the textual job descriptions in my dataset. I can use these job descriptions to classify employees into two groups—employees with impact on risk-taking and other employees. Employees are labeled as having impact if their job descriptions contain one of the following stemmed words: *loan*, *mortgag*, *credit*, *risk*, or *sale*. I then calculate my W-index for both subsets of employees—those with impact and the others. I show in Panel C of Table 3.11 that the W-index is related to my performance measures of stock return in crisis and percentage of charge-offs in crisis only for those employees with impact. Also, as expected, I find that volatility is positively related to the W-index of the impactful employees, but not the others.

The fact that the relationship between my workforce measures and performance is driven by employees with impact and not by other employees adds credence to the hypothesis that the relationship between human capital and crisis performance is not due to some proxy for risk-taking unrelated to workforce characteristics.

Table 3.11: Job descriptions and employees with impact

Panel A: Most frequently used words in job descriptions

Word	Freq. (%)	Word	Freq. (%)	Word	Freq. (%)	Word	Freq. (%)	Word	Freq. (%)
manag	46.2	respons	13.2	assist	10.9	risk	9.0	branch	7.4
busi	22.3	process	13.0	support	10.6	perform	8.7	mortgag	7.4
bank	20.4	client	12.9	offic	10.6	provid	8.0	train	7.3
servic	19.0	financi	12.8	relationship	10.5	execut	8.0	amp	7.1
presid	17.4	custom	12.6	project	10.4	system	8.0	intern	7.0
vice	16.8	loan	12.3	market	10.0	ensur	7.8	invest	6.8
develop	16.6	oper	12.2	account	9.9	implement	7.7	review	6.8
team	15.1	analyst	12.0	work	9.9	consult	7.6	commerci	6.6
product	13.6	includ	11.8	report	9.6	lead	7.6	program	6.6
senior	13.3	sale	11.4	credit	9.2	plan	7.5	complianc	6.6

Panel B: Top five keywords in LDA topics

	Keywords identified by LDA
Topic 1	loan, mortgag, account, process, review
Topic 2	risk, financi, invest, manag, bank,
Topic 3	custom, manag, sale, servic, busi
Topic 4	system, applic, support, data, test
Topic 5	student, assist, program, design, research
Topic 6	director, real, estat, commerci, manag
Topic 7	manag, project, develop, busi, team
Topic 8	event, recruit, medium, work, commun
Topic 9	presid, manag, vice, senior, consult

Table 3.11: Job descriptions and employees with impact (Continued)

Panel C: Crisis performance and employees with impact

	Stock return in crisis	% of charge-offs in Crisis	Volatility in 2003–2006
	(1)	(2)	(3)
W-index: employees with impact	-0.097***	0.002*	0.001**
	[0.035]	[0.001]	[0.000]
W-index: other employees	-0.051	0.000	0.000
	[0.033]	[0.001]	[0.000]
Book-to-market	-0.334*		0.000
	[0.182]		[0.002]
Beta	1.222***		0.028***
	[0.411]		[0.003]
Leverage	0.01		0.000**
	[0.017]		[0.000]
Net interest margin		0.296***	
		[0.063]	
Assets quintile FEs	Yes	Yes	Yes
Observations	200	201	202
R-squared	0.267	0.163	0.61

Notes: Panel A reports the stems of words used most frequently in job descriptions of bank employees in my sample. The stems are sorted by the fraction of job descriptions in which they are used. *Panel B* reports the top five keywords for topics identified by Latent Dirichlet Allocation (LDA) model of topic discovery. *Panel C* reports results of cross-sectional OLS regressions relating bank crisis performance and pre-crisis volatility to workforce characteristics. Bank performance is measured as buy-and-hold stock returns from June 2007 to December 2008 and fraction of loans charged-off in 2007–2009. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). The W-index is measured separately for "employees with impact" and other employees. Employees are classified as having impact if their job descriptions contain word stems: *loan*, *mortgag*, *credit*, *risk*, or *sale*. Bank equity beta is measured during 2004–2006. Book-to-market, leverage, assets, net interest margin are measured at the end of fiscal year 2006. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

3.9 Performance in the 1998 Crisis

My baseline result and subsequent analysis suggest that workforce characteristics can be used as an indicator of a bank's propensity to take on risk and its vulnerability to crisis. Fahlenbrach et al. (2012) show that banks' vulnerability to crisis is persistent in its own right. In particular, they document that a bank's stock return in the 1998 crisis is a strong predictor of its performance in the recent financial crisis. They suggest that this relationship demonstrates the persistence of banks' risk culture or some aspects of their business models. Since there is some support for the W-index capturing vulnerability to crisis through the same channel, I next use both the 1998 crisis return and the W-index as of year-end 1997 to predict bank performance in the recent crisis.[69]

Column 1 of Table 3.12 successfully replicates the baseline effect of Fahlenbrach et al. (2012) in the subsample of banks for which I have workforce composition data in 1997. The 1998 crisis return is set equal to the buy-and-hold return from August 3, 1998 to the date when a stock achieves its lowest value in 1998. Column 2 of Table 3.12 illustrates that the W-index as of as early as 1997 is still negatively related to the performance in the recent financial crisis. The two measures are controlled for simultaneously in Column 3. The magnitudes of both are reduced, and the statistical significance of the 1998 crisis returns decreases relatively more—to the 10% level. This is consistent with the notion that the W-index in fact captures a persistent component of a bank's risk culture that has an effect on performance, even a decade removed.

[69] As noted previously, since the professional networking platform did not exist in 1997, I rely on information that individuals retroactively filled out when they created their pages.

Table 3.12: The persistence of banks' vulnerability to crisis

	(1)	(2)	(3)	(4)
1998 crisis return	0.821***		0.584*	0.451
	[0.291]		[0.331]	[0.305]
W-index as of 1997		-0.100***	-0.076**	-0.144***
		[0.032]	[0.035]	[0.042]
Δ W-index from 1997 to 2006				-0.131***
				[0.049]
Book-to-market	-0.594**	-0.728**	-0.659**	-0.731**
	[0.277]	[0.309]	[0.299]	[0.321]
Beta	1.544**	1.964***	1.793**	1.610**
	[0.764]	[0.672]	[0.709]	[0.705]
Leverage	-0.021	-0.015	-0.019	-0.01
	[0.033]	[0.034]	[0.032]	[0.032]
Assets quintile FEs	Yes	Yes	Yes	Yes
Observations	95	95	95	95
R-squared	0.323	0.33	0.355	0.404

Notes: This table reports results of cross-sectional OLS regressions relating bank performance during the crisis of 1998 and workforce characteristics to performance in the recent financial crisis. *1998 Crisis Return* is the bank's stock return from August 3, 1998 until the day in 1998 on which the stock price attained its lowest value. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). W-index is measured as of year-end 1997. Model 3 includes both the 1998 crisis return and the W-index as independent variables. Model 4 includes an additional variable, the change in bank workforce characteristics between the two crisis periods. The change in the W-index is computed as the difference in the W-index between year-end 1997 and year-end 2006. Bank equity beta is measured from 2004 to 2006. Book-to-market, leverage, and assets are measured at the end of fiscal year 2006. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

I also explore the time series variation of the W-index in Column 4 of Table 3.12. In particular, I include a control variable equal to the difference between the W-index in 2006 and the W-index in 1997 for the same bank. The point estimate on that variable is negative and significant. This result suggests that not only does the level of the W-index in 1997 matter for the recent financial crisis performance, but also the change of the W-index in the intervening period between the two crises is relevant. Interestingly, the significance of the 1998 crisis disappears once we include this change in W-index as an added control.

Table 3.13: Bank performance in the 1998 crisis

	1998 Crisis Stock Return	Volatility 1H 1998	Volatility 2H 1998
	(1)	(2)	(3)
W-index	-0.036***	0.000	0.003*
	[0.013]	[0.001]	[0.002]
Book-to-market	0.176**	-0.005	-0.007
	[0.086]	[0.003]	[0.008]
Beta	-0.079*	0.001	0.006**
	[0.045]	[0.002]	[0.003]
Leverage	-0.029***	0.001	0.001
	[0.009]	[0.000]	[0.001]
Assets quintile FEs	Yes	Yes	Yes
Observations	97	97	97
R-squared	0.362	0.267	0.353

Notes: This table reports results of cross-sectional OLS regressions relating bank performance during the crisis of 1998 to workforce characteristics. *1998 Crisis Return* (Model 1) is the bank's stock return from August 3, 1998 until the day in 1998 on which the stock price attained its lowest value. *Volatility* of daily stock returns in the first and second halves of 1998 is studied in Models 2 and 3, respectively. The workforce characteristics are (a) having an MBA degree, (b) having a degree from a top 50 university, (c) job turnover, defined as the negative of current job tenure and (d) job jumper, defined as changing jobs more frequently than a median employee with similar career length. These workforce measures are aggregated to the bank level, adjusted by bank size, and standardized. The *W-index* is the standardized sum of four size-adjusted workforce characteristics (*MBA, Top School, Turnover,* and *Job Jumper*). Bank equity beta is measured during 1995–1997. Book-to-market, leverage, assets, and workforce characteristics are measured at the end of fiscal year 1997. All specifications include fixed effects for assets quintiles. Robust standard errors are reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

Table 3.13 relates the 1997 W-index to the 1998 crisis return. If the W-index is in fact a measure of a bank's risk appetite, it should be indicative of a bank's vulnerability not only to the recent financial crisis, but also to the 1998 crisis—even though the two differed in their fundamental causes. My results are consistent with this hypothesis. Column 1 shows that the 1997 W-index is a statistically significant predictor of the 1998 crisis return. Columns 2 and 3 confirm that this relationship is attributable to the crisis event. In particular, I show that only in the second half of 1998—and not in the first half—does volatility of stock returns have a statistically significant relationship with the W-index.

3.10 Conclusion

I find that banks with a higher proportion of employees with certain characteristics—MBA and top school degrees, tendency to shift jobs and shorter job tenures—perform worse during periods of crisis. A one standard deviation increase in the fraction of MBAs lowers stock returns between July 2007 and December 2008 by 4.5 percentage points. Similar statistics for top degree holders, workers with short tenures, and job jumpers are 9.4 percentage points, 13.5 percentage points, and 12.2 percentage points, respectively. A one standard deviation increase in the W-index—the standardized sum of the other four measures—is related to a 14.5 percentage point decrease in stock returns during the recent financial crisis. The results are similar for bank failures and for the fraction of loans charged-off in crisis.[70]

My results are not explained by the fact that banks grew tremendously in the pre-crisis period and tended to hire individuals with the aforementioned characteristics. I find a strong relationship between crisis performance and the W-index even if I calculate the latter using the workforces of banks at the turn of the century. This suggests that there are persistent qualities of banks' workforces that are predictive of their vulnerability to crisis. My results are not, however, capturing a difference between "good banks" with strong performance in times of boom and bust alike, and "bad

[70] The relationship I document between bank performance and workforce characteristics cannot be attributed to my workforce measures proxying for observable bank characteristics like assets growth, loan portfolio composition, and residual compensation, among others.

banks" that consistently underperform. Rather, banks that score highly on my workforce measures tend to be above-average performers in the pre-crisis period, but perform poorly after crisis onset.

I show that high W-index banks had a predisposition to take on risk in the pre-crisis period as measured by the ratio of highly rated securitization tranches to assets, the ratio of private mortgage-backed securities to assets, and the interest rates on loans. They also had higher volatility and tail risk, relatively poor risk management, and engaged in more securitization. These results support the hypothesis that workforce characteristics are capturing aspects of banks' risk appetites.

When extrapolating my results to the 1998 crisis, I find that the same workforce measures that are able to predict which firms will perform well in the Great Recession also predict outcomes in the earlier crisis, despite its fundamentally different nature. I find evidence consistent with the notion that the persistence of banks' vulnerability to crisis can be explained by the stickiness of their workforce characteristics, which in turn may capture components of their underlying risk cultures.

My findings demonstrate that looking to workforce measures can be a powerful indicator of banks' vulnerability to crisis. These measures are especially valuable in an industry like finance, where banks are easily able to obscure their financial capital in order to obfuscate any problematic signals from their investors and the public at large. Human capital, on the other hand, is much harder to disguise, and this paper manifests its importance in demonstrating which firms will succeed—and which will fail—in times of tumult. One natural question that merits further consideration is whether this relationship has especially strong predictive power in firms where obscurity is at its most extreme.[71]

Taken together, the results in this paper suggest that workforce composition sheds light on the elusive "*quantifiable information about a bank's risk culture or business model that could be used to measure its sensitivity to crises*" that Fahlenbrach et al. (2012) remain in search of at the end of their analysis.[72]

[71] Measures of firms' obscurity are tantamount to, for example, the disagreement among analysts about expected earnings (Diether, Malloy, and Scherbina 2002) or information processing complexity (Cohen and Lou 2012).

[72] The last paragraph in the conclusion of Fahlenbrach et al. (2012) reads as follows: "In the absence of quantifiable information about a bank's risk culture or business model that could be used to measure its sensitivity to crises, our evidence shows that there is strong persistence in crisis exposure for crises that are 10 years apart so that a bank's performance in one crisis is an important measure of its inherent riskiness and exposure to crises."

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